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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 tackle this puzzle by measuring 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.

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 relative mobility, captured by the GGC, is perhaps the most salient and robust finding of this literature. This relationship has been documented not only across countries, but also across regions or geographic units within countries.

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 observed 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);Shiue (2025). 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 over the same time period. While measuring *changes* in mobility is notoriously difficult, the existing evidence points towards at most small decreases in intergenerational mobility in the US over the most recent decades. Whereas Aaronson and Mazumder (2008) and Davis and Mazumder (2026) report a decrease in mobility during the 1980s, Lee and Solon (2009) find no large changes for cohorts born between 1952 and 1975. Similarly, Chetty et al. (2014b) conclude that "children entering the labor market today have the same chances of moving up in the income distribution (relative to their parents) as children born in the 1970s"(p.141). Song et al. (2020) even find stable intergenerational elasticity coefficients since the early 20th century.[5] Given the large scale of the increase in inequality observed since 1980, the Great Gatsby Curve might have suggested that a large decrease in mobility should have materialized. However, the evidence for this so far has been mixed at best.

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.

The relationship between *changes* in inequality and *changes* in socioeconomic mobility, something that henceforth we call the "dynamic GGC", has been studies much less in the existing literature. Two notable exceptions are Brandén (2019), who studies the GGC across Swedish commuting zones and in some specifications includes commuting zone fixed effects, showing the existence of a dynamic GGC in Sweden. More directly, a more recent paper by Grebol et al. (2025) shows both a static and dynamic GGC in education in Spain. The

[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 is beyond the scope of our paper. Also note that the lack of decline in relative mobility over the last decades does not stand in contrast to a documented decline in mobility over longer time periods: Long and Ferrie (2013) for example have documented a decline in mobility in the US since the late 19th century. Consistent with this, Feigenbaum (2018) finds high mobility for Iowa in the early 20th century. Song et al. (2020) show an increase in relative mobility during the late 19th century, followed by a long period of little to no change since the early 20th century.

relative dearth of evidence on the dynamicy of the GGC 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 over long time periods 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.

This paper provides what is, to the best of our knowledge, the first systematic empirical study of the *dynamic* relationship between inequality and socioeconomic mobility in the United States. We directly measure the dynamic GGC across US counties at both "short" intervals of two decades, and over a longer period of over a century.[6] 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. Using crosswalks from Abramitzky et al. (2020) and Helgertz et al. (2023), 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.

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. Had the Great Gatsby been a real-life person, instead of a fictional one, he would be part of our micro-data. Our unit of observation is the county where the son grew up, i.e. the one where we observe both father and son in the earlier census. We compute county-level measures of intergenerational persistence as the average correlation of father-son incomes at the county level. We further measure county-level inequality as the dispersion in individual incomes as reflected by each county's Gini coefficient.

The above procedure allows us to perform the exercise of correlating changes in inequality with changes in socioeconomic mobility over the period 1880 to 1940. However, in order to evaluate the dynamics of the GGC over the long run we need to merge our panel with contemporaneous data on inequality and socioeconomic persistence at the level of US counties. To this aim, we develop a methodology that allows us to study the dynamic GGC over the long-run. We propose new unit-less measures of inequality and socioeconomic mobility at

[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).

the level of US counties that allow us to align historical census data with the modern county level data on inequality and socioeconomic mobility assembled by Chetty et al. (2014a).

The main difficulty in linking our panel using historic data with recent measures of inequality and socioeconomic mobility lies in the fact that the measures employed for both inequality and mobility differ across datasets. To address this challenge we propose using the county-level ranks within the overall US distribution, separately along the inequality and socioeconomic mobility dimensions, as alternative measures of inequality and socioeconomic mobility across US counties.[7]

Using these novel measures allows us to extend our analysis over the entire period 1880 to 2010. We validate these alternative measures against more traditional measures of inequality and socieconomic persistence by using them to study the static and short-run dynamic GGC, and uncover similar results as those obtained with more traditional measures. We then employ our novel measures to study the long-run dynamic GGC.

Our findings paint a subtle picture of the relationship between inequality and socioeconomic mobility over the course of the 20th century. We show that across the universe of US counties, changes in inequality over 20 year intervalls do **not** correlate in a systematic way with changes in intergenerational income mobility. This aligns with the current US experience and the explanation offered Becker et al. (2018). Over the longer 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 more reminiscent of the static GGC.[8] This would seem to support to a version of the naive 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. The overall picture is, thus, pessimistic: the fact that mobility has not fallen *yet* is perfectly consistent with the historical record. However the historical record also suggests that over the longer run, the relationship between inequality and socioeconomic persistence is likely to reassert itself, eventually materializing 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

[7]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.

[8]Durlauf et al. (2022) and Berman (2019) show that a sizable part of the static GGC might be due to a mechanical relationship between immobility (measured via the IGE) and inequality (measured via the variance of log income in Durlauf et al. (2022) and the gini coefficient in Berman (2019)). However, their arguments pertain to steady state relationships in levels and leave the question of dynamics open. In addition, it is also not clear how the mechanic relationship found by both papers extends to the rank-based measures used by us.

measures of inequality and intergenerational mobility. In section 4 we outline our main results, and in section 5 we discuss their implications and conclude.

2 Data

To measure our key variables of interest, income inequality and intergenerational socioeconomic mobility, we link men across censuses using the full count US censuses available for the late 19th and early 20th centuries from IPUMS (Ruggles et al. (2021)). To link people across censuses, we draw on the crosswalks provided by Abramitzky et al. (2020). These are based on a fully automated approach that creates links based on standardized first and last names, as well as age. To minimize the risk of false positives, we use the more conservative matching procedure that merges based on exact names and requires matches to be unique within two years around the birth year. In the Appendix, we show that our results are robust to alternatively using links from Helgertz et al. (2023). These are based on a probabilistic approach that employs machine learning techniques and also incorporates information on birthplace and family/household characteristics.

To make the sample of matched individuals more representative of the overall population, we follow the suggestion of Bailey et al. (2020) and Abramitzky et al. (2021a) and weight observations by their predicted probabilities of being matched. Specifically, we run a probit model where the outcome variable is an indicator variable that codifies whether an individual can be matched to his father 20 years earlier. As explanatory variables, the model uses state of residence dummies, an indicator for living in an urban area, age dummies, race dummies (black, white, and other), and dummies for bins in the IPUMS earnings score variable. We employ the model to calculate the predicted probability of being matched for each observation, and then calculate the weight of each observation as $\frac{1-\hat{p}}{\hat{p}}\frac{x}{1-x}$, where x is the share of matched individuals in the census when the son is an adult, and $\hat{p}$ is the predicted probability of being matched. We then use these weights as probability weights when computing county-level indicators such as the Gini and the IGE.[9] 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 also link women across censuses and finds that mobility patterns for married men and married women are very similar.

[9] We calculate separate weights for sons where the father can be matched to two previous observations in the census, which we use for robustness checks.

We use the census links from Abramitzky et al. (2020) 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) to construct an individual-level income measure. We regress 1940 (log-) wage income on dummies that interact occupation with state of residence, race[10] 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. Similar imputations based on occupation and other variables have also been used by Abramitzky et al. (2021b) 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.

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. (2021b). We use data on the total income of farmers and farm 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.[11] 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 modern outcomes, we draw on measures of intergenerational persistence and inequal-

[10] Black, White, and Other

[11] 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 is still often erroneous. We therefore do not use it.

ity calculated by Chetty et al. (2014a). Using federal income tax data for parents over the years 1996-2002 and for their children in 2011 and 2012, Chetty et al. (2014a) 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 income measure described above, we proceed to construct measures of intergenerational socioeconomic mobility at the county×interval level (where intervals represent the 1880-1900, 1900-1920 and 1920-1940 periods). 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"). 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.

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

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. (2014a), 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}. 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 percentile rank of county c on each of the measures of persistence (ρ_{ct}) at time t. This county-ranking procedure is applied separately

	Mean	Standard dev	Obs
IGE 1900	0.356	0.165	2,037
Gini fathers 1900	0.255	0.078	2,037
IGE 1920	0.366	0.161	2,515
Gini fathers 1920	0.262	0.071	2,515
IGE 1940	0.362	0.130	2,951
Gini fathers 1940	0.280	0.072	2,951
Rank ranks slope 2000	0.331	0.072	2,769
Gini parents 2000	0.384	0.086	2,769
Δ IGE 1920-1900	0.019	0.172	2,022
Δ Gini Fathers 1920-1900	0.011	0.056	2,022
Δ IGE 1940-1920	0.003	0.147	2,508
Δ Gini Fathers 1940-1920	0.023	0.047	2,508

Table 1: Summary statistics

to our two measures of socioeconomic persistence: the intergenerational elasticity of income and the father-son rank-rank correlation.

To measure inequality, we calculate the Gini coefficient among fathers for each county c and time t. Similarly to Chetty et al. (2014a), we include only the fathers of the father-son pairs that are used in the IGE calculation in our Gini calculation. However, in the Appendix, we show that our results are similar when we instead calculate the Gini for the full male county population aged 17-65 in the sons' childhood periods.[12] We also calculate an analogous unitless measure of inequality for the purposes of long-run analysis: the percentile rank of counties by inequality at each point in time. 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 income at the 90th percentile and the log of income at 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

[12]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 0.67, indicating a 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 0.56.

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[13].

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 two different measures of ρ: The intergenerational correlation in earnings and the rank-rank coefficient in earnings. Additionally, we estimate the same equation using our county-rank measures of persistence $rank\rho_{ct}$ and inequality $rankI_{c,t-20}$. We run all regressions separately for each interval.[14]

3.3 Dynamic GGC

To study how the relationship between inequality and socioeconomic mobility evolves over time, we calculate the changes in inequality and socioeconomic persistence for each county over each time interval. We then correlate these changes to study the dynamic relationship between persistence and inequality (which we call the Dynamic GGC):

We define the changes 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 run the following regressions:

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

[13]The patterns of socioeconomic mobility depicted here are also similar with those documented for this period by Connor and Storper (2020) and Tan (2023) using measures of upward mobility.

[14]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 10% of counties in terms of the number of observations used to construct these variables. This removes counties with fewer than 64 observations.

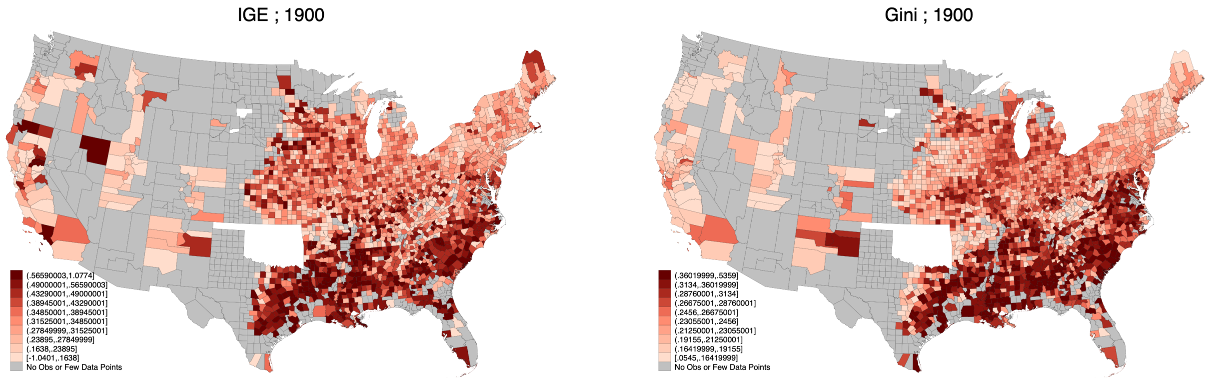


Figure 1: Geographical distribution of social mobility (measured via the IGE between fathers in 1880 and sons in 1900) inequality (measured via the Gini coefficients of fathers in 1880). County borders are from Manson et al. (2023) and based on 1880 boundaries.

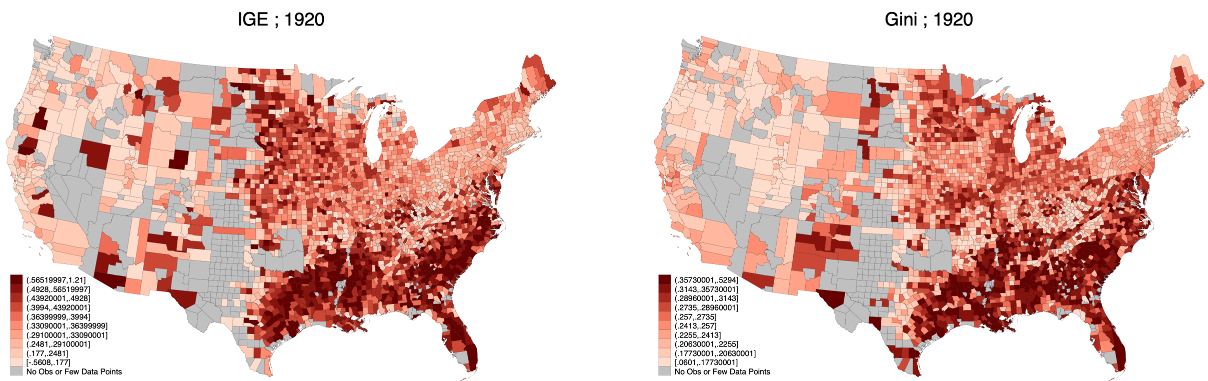


Figure 2: Geographical distribution of social mobility (measured via the IGE between fathers in 1900 and sons in 1920) inequality (measured via the Gini coefficients of fathers in 1900). County borders are from Manson et al. (2023) and based on 1900 boundaries.

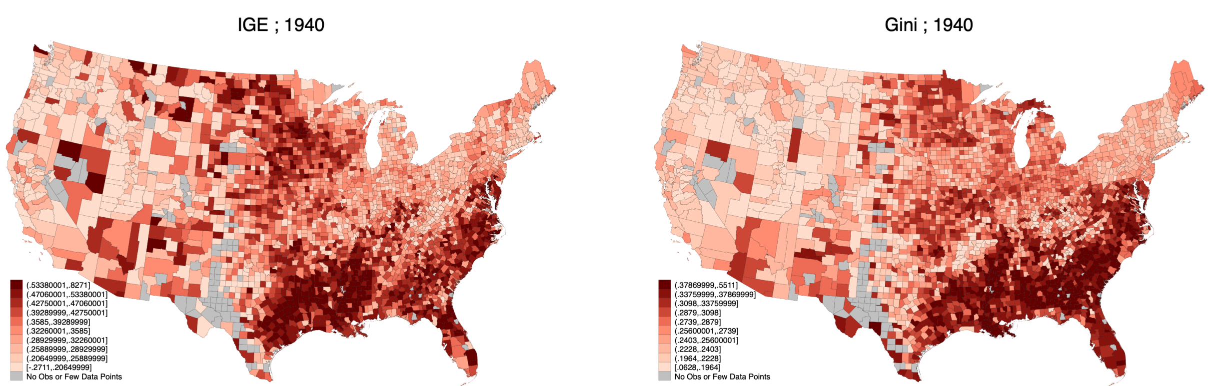


Figure 3: Geographical distribution of social mobility (measured via the IGE between fathers in 1920 and sons in 1940) and inequality (measured via the Gini coefficients of fathers in 1920). County borders are from Manson et al. (2023) and based on 1920 boundaries.

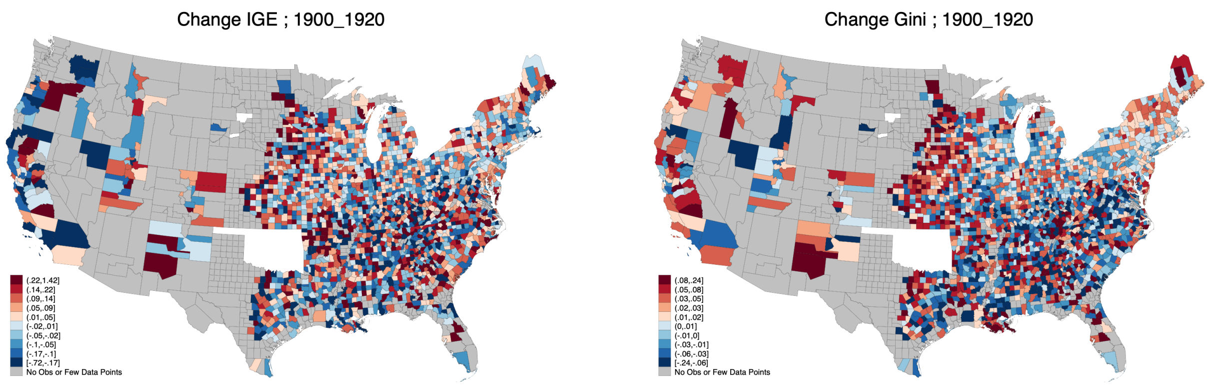


Figure 4: Geographical distribution of changes in social mobility between 1900 and 1920 and changes in inequality among fathers 1880 and 1900. County borders are from Manson et al. (2023) and based on 1880 boundaries.

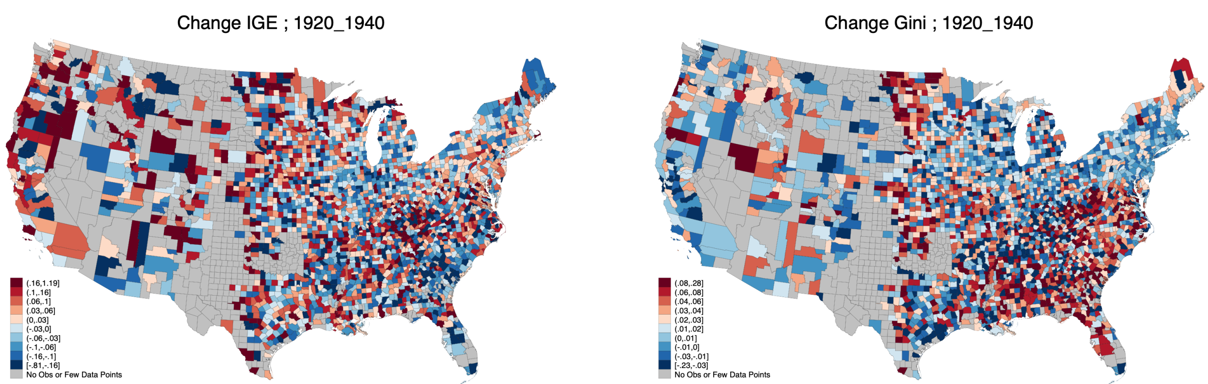


Figure 5: Geographical distribution of changes in social mobility between 1920 and 1940 and changes in inequality among fathers 1900 and 1920. County borders are from Manson et al. (2023) and based on 1920 boundaries.

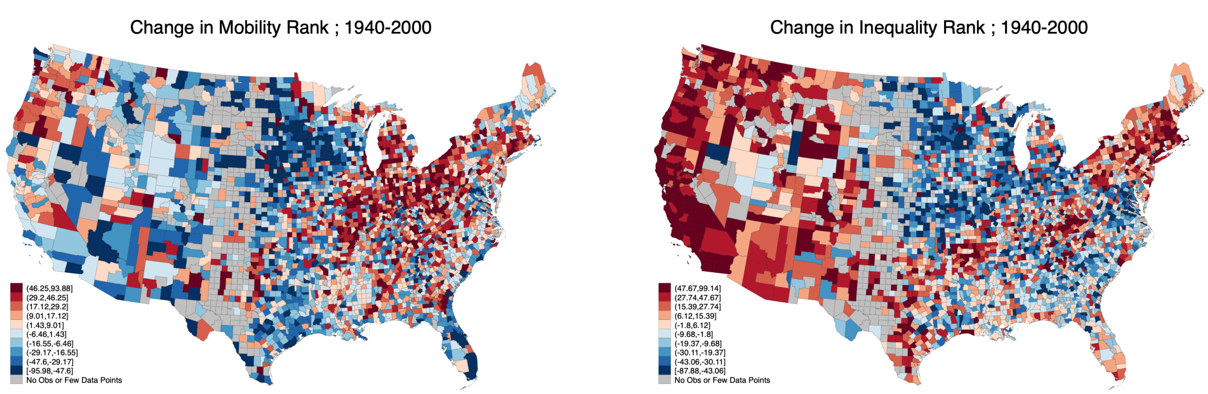


Figure 6: Geographical distribution of changes in counties' mobility and inequality ranks between 1940 and 2000. County borders are from Manson et al. (2023) and based on 1920 boundaries.

where the parameter of interest is δ_t, which captures the slope of the relationship between changes in inequality and changes in 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 also that the models in 3 do 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 aim to combine our measures of inequality and persistence for the 1900-1940 period with modern measures of inequality and mobility across US counties provided by Chetty et al. (2014a). While the data Chetty et al. (2014a) is based on actual income measures from tax returns, our measures are based on wage predictions for the period 1900-1940 that only capture variation due to occupation, age, race, and state of residence and thus disregard any additional 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. We make use of our novel county-rank-based measures of inequality and mobility to compute the long run changes in inequality and socioeconomic persistence across US counties, and study their co-movement.

This methodology is described formally below:

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

$$\Delta rank\rho^s_{ct} = \alpha^s_t + \delta^s_t \Delta rankI^s_{ct} + \epsilon_{ct} \tag{4}$$

where t and $s > t$ are two periods over which we evaluate the changes in persistence and inequality at the county level (i.e. we compute $\Delta rank\rho^s_{ct}$ and $\Delta rankI^s_{ct}$ respectively for each county c). The key coefficient of interest is δ^s_t which captures the slope of the dynamic "Great Gatsby Curve" over the period t to s.

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 the 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. (2014a)). 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 either measure to result in similar rankings when derived from data resulting from the same data generating process.[15]

In other words, we expect that, were the high-quality tax data used by Chetty et al. (2014a) 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 the changes in the county ranks in terms 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.

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 income 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) 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).

Across all specifications, we recover the positive association between intergenerational socioeconomic persistence and inequality that has been documented elsewhere for more recent

[15] 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 likely 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
County Level	0.77***	0.86***	0.81***	0.90***	0.81***	0.77***	0.24***
	(0.05)	(0.05)	(0.03)	(0.05)	(0.05)	(0.04)	(0.02)
County Rank	0.37***	0.40***	0.45***	0.40***	0.37***	0.39***	0.33***
	(0.02)	(0.02)	(0.02)	(0.02)	(0.02)	(0.02)	(0.02)
Num. Counties	2,037	2,515	2,951	2,037	2,515	2,951	2,769
Year	1900	1920	1940	1900	1920	1940	2000

Robust std errors in parethenses.

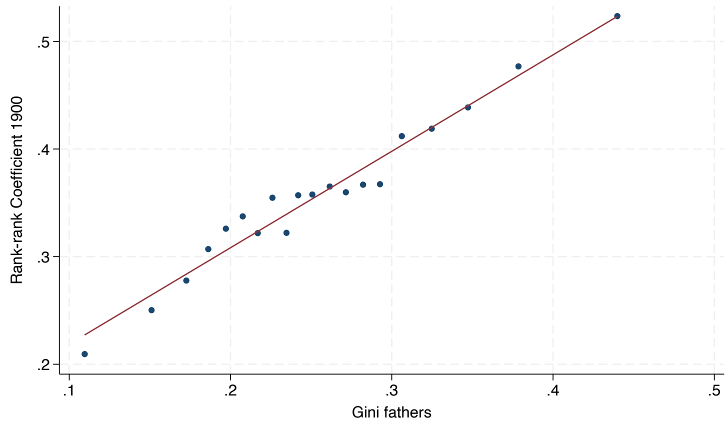
Table 2: Static Great Gatsby Curves

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. (2014a) 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*), or by the correlation of the earnings rank of the father with the rank of the son (4, 5, 6, 7, marked *r-r*).).
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.

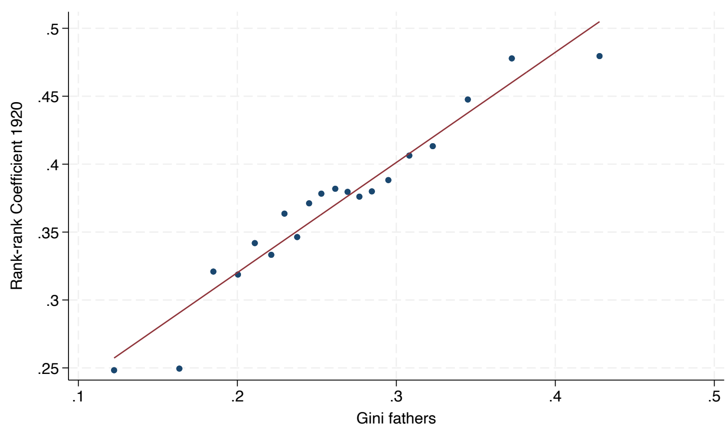
time periods. As it is the case nowadays, one hundred years ago more unequal US counties tended to display more intergenerational persistence, irrespective of the measures of intergenerational persistence we use. Indeed, the strength of the association seems if anything stronger for the first half of the twentieth century than for the more recent past[16], though caution is advised when interpreting coefficient magnitudes given the limitations of our historical income measures. Results when using either the IGE or the rank-rank correlation are very similar. This echoes the finding of Deutscher and Mazumder (2023) that these two measures of relative mobility are highly correlated. The Great Gatsby Curve is also apparent when looking at Figures 7a - 7c. 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 idea that inequality is associated with greater social mobility is not only rejected today: this relationship was already not present during the Great Gatsby era.

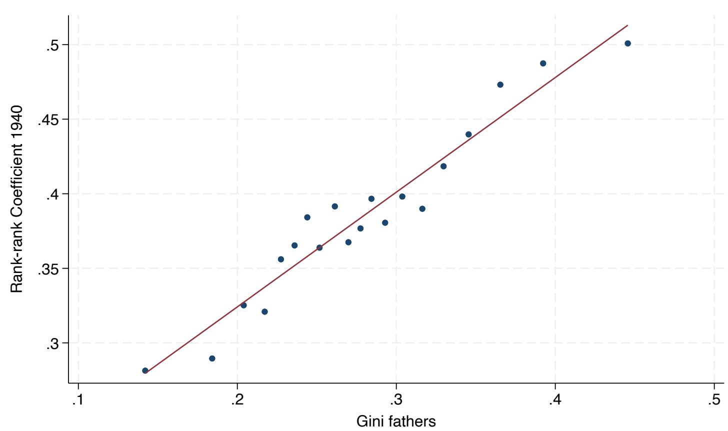
[16]This can be seen by comparing coefficient magnitudes in columns 4 to 6 in Table 2 to those in column 7.



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



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



(c) Levels. r-r 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.

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.*

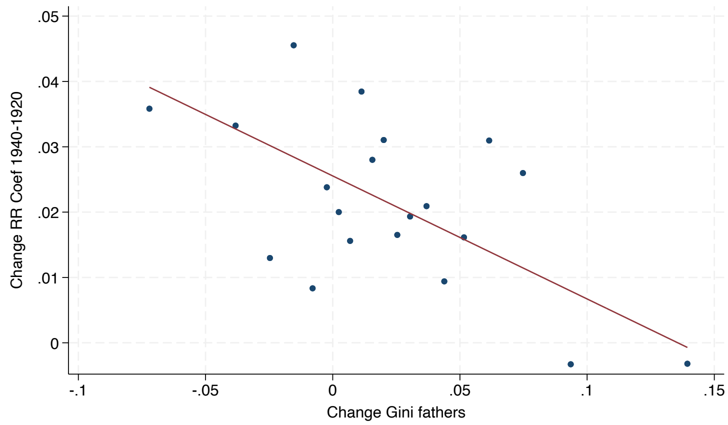
Reassuringly, our results concerning the Great Gatsby Curve are qualitatively similar when we employ our novel methodology based on county ranks (see second row of Table 2). Both in the early twentieth century and closer to the present, counties that ranked highly in terms of inequality also tended to rank highly in terms of intergenerational socioeconomic persistence, irrespective of the underlying measures of persistence used to construct the rankings. As in the analysis with more established measures, the positive association between inequality and intergenerational persistence 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 in support of 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 not always positive (i.e. the "Dynamic" GGC is unstable over this period).*

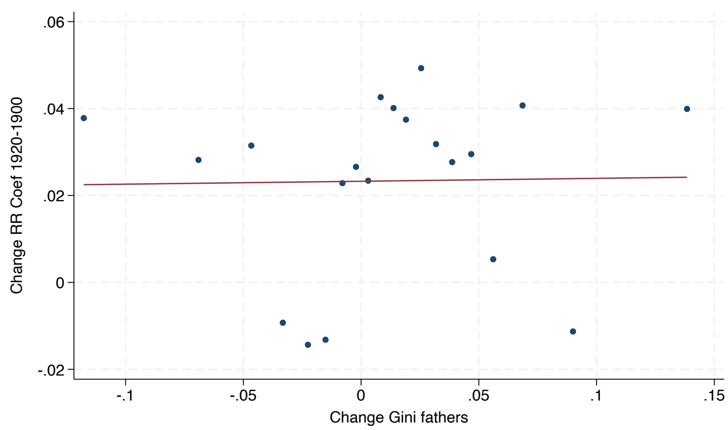
Table 3 outlines our results regarding the relationship between *changes* in inequality and *changes* in intergenerational socioeconomic persistence (which we call the "Dynamic" GGC). Similarly to our discussion of the "Static" GGC, the first row of Table 3 presents our results employing established measures of income inequality (i.e. the Gini Coefficient) and socieconomic mobility (the IGE and the rank-rank correlations between fathers and sons), while the second row of the table presents results employing our novel measures of inequality and intergenerational socioeconomic mobility using county ranks.

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 significantly related to changes in intergenerational income persistence, with very low point estimates that change sign across different measures for mobility. 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 to be much more noisy than the static GGC.

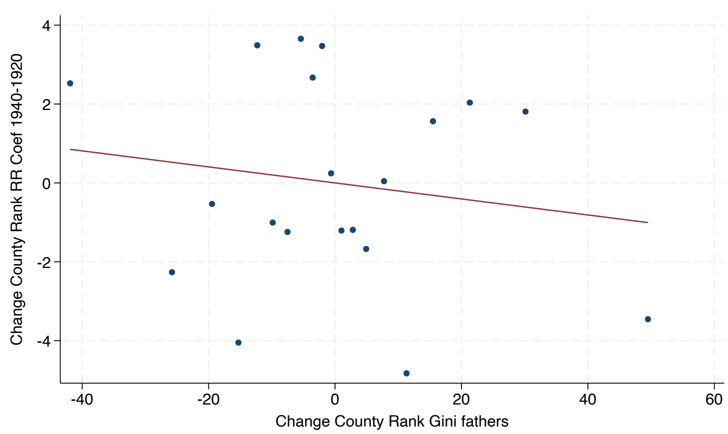
Result 4 *Evaluating the correlation between changes in inequality and changes in socioeconomic persistence using our novel measures based on county ranks produces similar results.*



(a) Levels. Δr-r vs ΔGini, 1920-1940



(b) Levels. Δr-r vs ΔGini, 1900-1920



(c) 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.

	(1) ΔIGE	(2) Δr-r	(3) ΔIGE	(4) Δr-r	(5) Δr-r	(6) Δr-r
Δ County Levels	-0.25***	-0.19**	-0.04	0.01		
	(0.09)	(0.10)	(0.10)	(0.11)		
Δ County Rank	-0.06*	-0.02	0.01	0.04	0.12***	0.13***
	(0.03)	(0.04)	(0.04)	(0.04)	(0.02)	(0.02)
Observations	2,508	2,508	2,022	2,022	2,663	2,350
Year	1940/1920	1940/1920	1920/1900	1920/1900	2010/1940	2010/1920

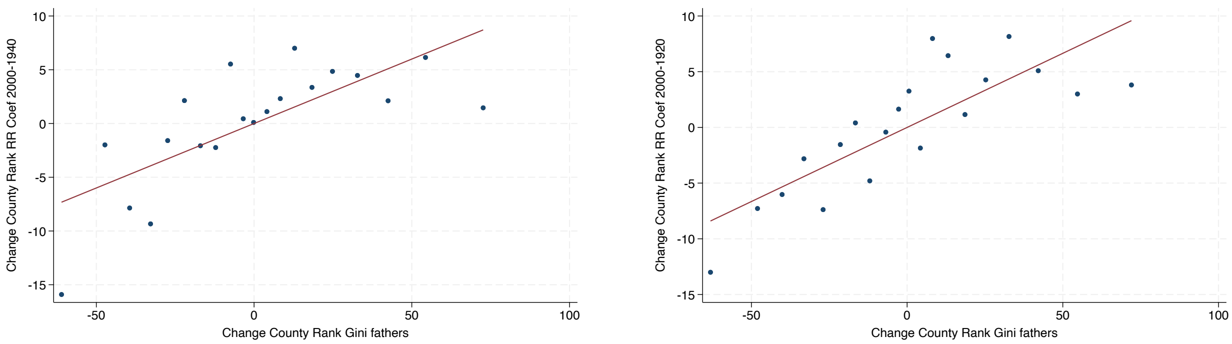
Robust std errors

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. (2014a) 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), or the correlation of the earnings rank of the father with the rank of the son (2, 4, 5, 6).
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.

The results in the second row of Table 3 (that can be visualized comparing figures 8a and A5a) provide further reassurance regarding the reliability of our novel measures in inequality and socioeconomic mobility based on county ranks. Our findings using these measures are similar to 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. For the period 1900-1920, the correlation between changes in inequality and changes in social mobility is close to zero and insignificant, while for 1920-1940 we continue to find a negative, but considerably weaker correlation. 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) 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.[17]

[17] One potential worry is that the lack of a short-run finding is driven by a lower of degree of measurement error in income inequality in the modern data compared to the historical data. In the Appendix, we provide simulation results suggesting that this is unlikely to be the case.

5 Discussion and 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.

To explain these apparently contradictory facts, we require advances on both the theoretical and empirical fronts. On the theoretical front, we require models that allow for the possibility that changes in inequality may not be reflected, at least for prolonged time periods, in changes in socioeconomic persistence. Becker et al. (2018) provide such a model, although arguably more work is warranted in this area.

On the empirical front, we require a more comprehensive view of the patterns of comovement between inequality and socioeconomic mobility over the long run. We need to understand if these variables present a systematic relationship over the long run, and if their recent behavior in the US context is unusual or not when set against the historical record. It is on this issue that we aim to contribute in this paper.

Our contribution is thus to provide empirical evidence about the relationship between inequality and socioeconomic mobility over the very long run. We obtained measures of intergenerational mobility and inequality for all US counties for a period expanding over 120 years and we showed that while the correlation of the levels of these variables is extremely robust (it was there 100 years ago as it is now) the correlation between changes in these variables is much more subtle.

During the course of the last century, changes in inequality did always 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 recent experience is perfectly consistent with the historical record, as Becker et al. (2018) suggested.

This finding should perhaps not offer great relief, however. The same historical record suggests a disturbing fact, which in many ways brings us back to the naive interpretation of the GGC: in the very long run (i.e. for periods longer than a century), changes in inequality do reliably correlate negatively with changes in income mobility, and the magnitude of the relationship is not dissimilar to that reflected by the static GGC.

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

Our contribution leaves unanswered several important questions that would benefit from future research. On the theoretical front, we believe our results motivate a search for theories that are able to accommodate both the presence of prolonged periods when changes inequality are unrelated to changes in socioeconomic mobility, while featuring mechanisms that explain the re-emergence of a negative relationship over the (very) long run. On the empirical front, further investigation of the dynamic GGC, perhaps over different time horizons and in different settings, would be helpful to determine the generalizability and robustness of our findings for the US over the late nineteenth and twentieth centuries.

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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. (2014a) 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 for 1920-1940, 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 and the re-emergence of the GGC in the long run. The only difference to our previous results is that for whites, there also seems to be a (weaker) dynamic GGC in the short run.

Our baseline results are based on father-son pairs that are linked by the Abramitzky et al. (2020). In order to reduce the risk of false links, we use the more conservative Abramitzky et al. (2020) approach that links based on place of birth, year of birth, and exact name and additionally requires the match to be unique within two years within a 5-year band around the birth year (also see Abramitzky et al. (2021a)). In table A10, we instead use links created by Helgertz et al. (2023) based on a probabilistic approach (see Helgertz et al. (2022) for details). These links are less conservative and produce a higher number of observation (for example, the 10th percentile cut-off for counties is now 94 instead of 64), but yield very similar results: Static GGCs for 1900, 1920, and 1940, an unclear dynamic picture over the short run, and a strong dynamic long-run GGC.

When calculating the Gini coefficient, we follow the approach of Chetty et al. (2014b) and calcualte them for fathers in our core sample, i.e. for the fathers of father-son pairs that are also included in the intergenerational analyses. In our case, this requires both father and son to be between 25 and 50 in the period when their income is predicted, and drops the father if either he or the son has a non-occupation occupation code or serves in the military. In table A11, we instead calculate the Gini coefficient in the fathers' generation among all males aged 17 to 65, dropping only those in the military and with non-occupation occupation codes. We find a dynamic GGC for 1900-1920, but no or even a negative one for 1920-1940, confirming our result of an unstable short-run dynamic GGC. The static and long-run dynamic GGCs, on the other hand, remain robust.

While the robustness of our results across different ways of measuring social mobility and inequality give us confidence that we do uncover a robust pattern, one remaining worry is the possibility of measurement error, especially in measuring inequality in the historical census data. This could in theory contribute or even explain several of our findings: Whereas the modern Gini coefficients from Chetty et al. (2014a) are based on precise tax data, our historical Gini coefficients are based on income imputations. If this leads to sizable measurement error in the levels and county ranks of the Gini coefficients in the historical data, this could produce attenuation bias, and particularly so when further differencing over time. This in turn might explain the null finding for the dynamic GGC, where our explanatory variable is the change in inequality. In addition, this attenuation would be worse in the short run, where we have the difference of two historical inequality measures with potential measurement error, compared to the long run, where at least the modern data can be plausibly thought of as precisely measured.

Of course, we cannot improve the precision of our historical data. However, we can add noise to the modern data and examine whether the finding of the dynamic long-run GGC vanishes. If, on the other hand, we were to find a positive dynamic long-run GGC even after perturbing the modern inequality measures, this would give us confidence that the weak results for the dynamic short-run GGC are not merely driven by measurement error in the historical data (or at least that the relationship is significantly weaker at short relative to long time intervals). To assess this, we try two different noise-generating processes. In a first step (perturbation 1), we add i.i.d noise from a normal distribution with the same standard deviation as the actual modern Gini.

$$Gini_c^{perturbed1} = Gini_c + e_c$$

That is, we double the variance of the modern Gini coefficients, resulting in a measure that is 50% measurement error. We repeat this 1,000 times, each time drawing new error terms e. The resulting average mean and average standard deviation of the perturbed Gini coefficients are shown in Table A12. We then calculate the county ranks and the difference with the 1940 Gini county ranks, and perform our Dynamic GGC regression (equation 4). Across 1,000 different error draws, we find an average coefficient of 0.06, compared to 0.12 in column 6 of table 3 (see also rows 1 and 2 of table A13). Thus, even adding an exceptionally large amount of measurement error to the modern data can at most weaken the Dynamic GGC result, but not make it disappear.

However, the previous argument can be criticized for increasing the overall variation in the modern Gini coefficients. A more likely scenario is that historical Gini coefficients are not only noisier, but also systematically lower, as our income imputation cannot account for within-occupation wage dispersion. Somewhat consistent with this, Table A12 shows that the modern Gini data have a higher mean and variance than the ones based on historical income imputations. Therefore, a potentially fairer comparison would be to add noise, while reducing the overall variation in the modern Gini data.[18] We do this by creating a second set of modern perturbed Gini coefficients, according to the formula

$$Gini_c^{perturbed2} = 0.6 \cdot Gini_c + 0.6 \cdot e_c$$

where e comes from a normal distribution that has the same standard deviation as the original $Gini_c$, and mean 0.10. This leads to a new variable that again is roughly 50% measurement error, but has a similar mean and standard deviation as the fathers' Gini coefficient for the 1920-1940 dataset. We then again recalculate ranks, rank changes, and run our main regression. Across 1,000 different draws, we again find a mean coefficient of

[18] This is of course an extreme argument- it is entirely conceivable that Gini levels and variation did go up between 1920/1940 and nowadays.

0.06 (row 3 of Table A13). Thus, scaling the modern Gini coefficients down and adding substantial measurement error again produces a clear dynamic GGC over the long run. We conclude that the absence of a dynamic GGC is likely not an artifact of measurement error.

The above robustness checks address measurement error by perturbing the county-level Gini coefficients directly. However, this approach may not fully capture the impact of measurement error present at the individual level in historical census data, which is then aggregated into inequality and mobility measures. To address this potential limitation, we perform an additional exercise that directly mimics the type of noise likely present in historical data imputations and also adds within-occupation dispersion, which is limited due to the predicted nature of wages.

The final effect on aggregate measures at the county level is not straightforward for a number of reasons. On the one hand, measurement error at the individual level can bias estimates of both inequality and intergenerational mobility, with the direction and magnitude of the bias depending on how the error interacts with the underlying distribution of wages. For example, while classical measurement error generally attenuates estimated regression coefficients, adding random noise to wages can actually inflate measured inequality, as it mechanically increases wage dispersion within counties. On the other hand, our estimation of the Great Gatsby Curve (GGC) relies on the county-level ranking of these statistics, and it is not immediately clear how individual-level perturbations affect the relative ordering of counties. In practice, when noise is added independently across individuals, the resulting impact on county ranks and cross-county comparisons may be limited, especially in larger samples where random shocks tend to average out. Ultimately, the net effect depends on the balance between the magnitude of the measurement error and the true variation across counties—an issue we investigate empirically in our simulation exercise.

Specifically, for our analysis sample of sons observed in 1940 and their fathers, we perturb both the father's and son's individual predicted log-wages by adding independent, normally distributed noise, where the variance of the noise is proportional to the within-county wage variance for each generation. We then exponentiate these perturbed log-wages to recover the "noisy" predicted wage variables:

$$\text{wage}_{\text{error}} = \exp\left(\log(\text{wage}) + \varepsilon\right), \qquad \varepsilon \sim N(0,\, \sigma^2_{\text{county}})$$

with ε drawn independently for each individual and generation. This approach maintains the structure of our data-generating process, reflecting the realistic scenario that errors occur at the micro-data level and propagate into county-level Gini and mobility estimates through aggregation.

We repeat this procedure for a range of noise magnitudes (up to values where the variance of the wage variable increases by more than 100% due to the added measurement error), and recalculate all county-level summary statistics, including the Gini index, inter-generational regression (IGM) coefficients, and the GGC relationship. The results, summarized in Figure A12, show that while the addition of substantial measurement error at the individual level attenuates county-level statistics as expected (panels (a) and (b)), the cross-county ranking of Gini coefficients remains remarkably stable—largely because i.i.d. measurement error increases inequality proportionally across counties. For mobility measures, the correlation between original and perturbed rankings declines more rapidly with increasing measurement error, but the effect is moderate. For example, a simulated shock that increases wage variance by 50% reduces the correlation in IGM rankings to 0.72, with a mean absolute difference in percentile rankings of 15.

Importantly, we also find that the (static) GGC coefficient is only modestly attenuated and does not vanish as a result of the measurement error added at the micro level (panel (c)). This is not surprising, given that i.i.d. measurement error has little effect on inequality rankings, which enter on the right-hand side of the GGC regression and drive attenuation bias. In contrast, error in the mobility rankings increases the standard error of the regression (panel (d)), but does not bias the estimated coefficient.

This result reinforces our earlier interpretation: the absence of a dynamic GGC cannot be attributed solely to measurement error in the construction of historical inequality measures. Instead, our findings indicate that the non-significant results for the dynamic GGC are more likely to reflect genuine differences in the underlying data, rather than being driven primarily by imprecise measurement. Naturally, this exercise has limitations—most notably, it cannot account for all possible forms of non-classical or systematic measurement error that may exist in historical sources (including those that are endogenous to the distribution of occupations or demographic characteristics across counties), nor does it fully capture all potential channels through which data quality might affect our estimates. Nevertheless, our results suggest that, under plausible forms and magnitudes of (exogenous) measurement error, our main conclusions regarding the (in)stability of the Great Gatsby Curve are robust.

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
- Dynamic GGC, IGE. Levels and County Ranks. Fig A4
- Dynamic GGC, r-r. Levels. Fig A5

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 A6
- r-r versus Gini, Levels and County Ranks. Fig A7
- 2011. r-r versus Gini, Levels and County Ranks. Fig A8
- Dynamic GGC, IGE. Levels and County Ranks. Fig A9
- Dynamic GGC, r-r. Levels and County Ranks. Fig A10
- Long Run Dynamic GGC, r-r. Levels and County Ranks. Fig A11

	Correlation coefficient for year		
	1900	1920	1940
Rank-Rank	0.935	0.903	0.960
IGE	0.952	0.949	0.969

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

	(1)	(2)
Persistence measure	IGE/r-r	IGE/r-r
County Rank	0.17***	0.16***
	(0.02)	(0.02)
Observations	2,663	2,350
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. (2014a). 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)	0.10***	0.09***	0.08***					
	(0.01)	(0.01)	(0.01)					
Δ(log(p90)-log(p10))				0.00		-0.04***		
				(0.02)		(0.01)		
County rank changes					0.01		-0.07***	0.16***
					(0.03)		(0.02)	(0.02)
Observations	2,037	2,515	2,951	2,022	2,022	2,508	2,508	2,663
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)	0.55***	0.56***	0.46***					
	(0.03)	(0.03)	(0.02)					
Δ(Var(LogIncome))				-0.09		-0.21***		
				(0.07)		(0.05)		
Change in County Rank					0.02		-0.07*	0.20***
					(0.04)		(0.04)	(0.02)
Observations	2,037	2,515	2,951	2,022	2,022	2,508	2,508	2,663
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	0.97***	0.90***	0.74***					
	(0.06)	(0.05)	(0.04)					
Δ(Gini Fathers)				0.07		-0.23***		
				(0.11)		(0.09)		
Change in county rank					0.01		-0.05	0.14***
					(0.04)		(0.03)	(0.02)
Observations	2,037	2,515	2,951	2,022	2,022	2,508	2,508	2,663
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	0.74***	0.82***	0.80***					
	(0.05)	(0.05)	(0.03)					
Δ(Gini fathers)				-0.14		-0.31***		
				(0.10)		(0.09)		
Change in County Ranks					-0.02		-0.09***	0.17***
					(0.04)		(0.03)	(0.02)
Observations	2,037	2,515	2,951	2,022	2,022	2,508	2,508	2,663
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.

	(1)	(2)	(3)	(4)	(5)
VARIABLES	IGE		Change in IGE	Change in County Rank	
Gini Fathers	0.91***	0.82***			
	(0.05)	(0.03)			
Δ(Gini Fathers)			-0.15*		
			(0.08)		
Change in county rank				-0.00	0.19***
				(0.03)	(0.02)
Observations	2,515	2,951	2,508	2,508	2,663
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.

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
VARIABLES	IGE	IGE	IGE	Δ IGE	Δ County Rank	Δ IGE	Δ County Rank	Δ County Rank
Gini fathers	1.21***	0.93***	0.90***					
	(0.11)	(0.10)	(0.08)					
Δ(Gini fathers)				-0.10		-0.25		
				(0.23)		(0.21)		
Change in County Ranks					-0.02		0.00	0.12***
					(0.04)		(0.04)	
								(0.02)
Observations	2,036	2,515	2,951	2,022	2,022	2,508	2,508	2,663
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	0.48***	0.44***	0.38***					
	(0.07)	(0.08)	(0.04)					
Δ(Gini fathers)				0.34***		0.08		
				(0.11)		(0.11)		
Change in County Ranks					0.10***		0.01	0.22***
					(0.04)		(0.03)	(0.02)
Observations	2,037	2,515	2,951	2,022	2,022	2,508	2,508	2,663
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	(2) IGE	(3) IGE	(4) Δ IGE	(5) Δ County Rank	(6) Δ IGE	(7) Δ County Rank	(8) Δ County Rank
Gini Fathers	1.14***	1.29***	1.17***					
	(0.05)	(0.05)	(0.03)					
Δ(Gini Fathers)				-0.20**		0.10		
				(0.09)		(0.09)		
Change in county rank					0.01		0.07**	0.16***
					(0.03)		(0.03)	(0.02)
Observations	2,124	2,481	2,895	2,468	2,468	2,102	2,102	2,350
Year	1900	1920	1940	1900/1920	1900/1920	1920/1940	1920/1940	1940/2010

Robust std errors

Table A10: Robustness to using links from Helgertz et al. (2023)
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	2.06***	1.61***	1.38***					
	(0.22)	(0.16)	(0.11)					
Δ(Gini Fathers)				0.48***		-0.44***		
				(0.18)		(0.14)		
Change in county rank					0.14***		-0.02	0.21***
					(0.04)		(0.02)	
Observations	2,036	2,515	2,951	2,022	2,022	2,508	2,508	2,663
Year	1900	1920	1940	1900/1920	1900/1920	1920/1940	1920/1940	1940/2010

Robust std errors

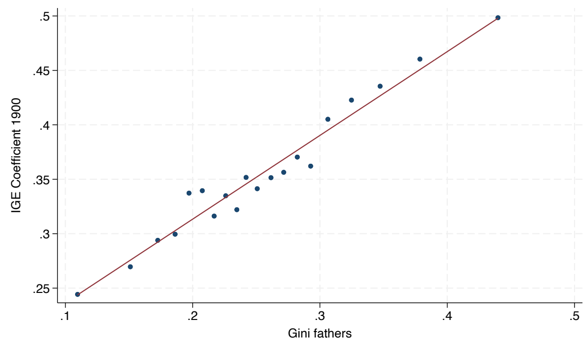
Table A11: Robustness to Gini population
Inequality is measured as the gini coefficient in income among everybody in the county aged 17-65 20 years before the measurement of the sons' incomes. Persistence is measured by the IGE. Rows 1-3 correlate the county persistence and the county inequality levels. 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.

	(1) Mean	(2) Standard dev (data)	(3) Average Mean (across 1,000 error draws)	(4) Average sd
Gini parents 2000	0.383	0.086		
Gini fathers 1940 (regression sample)	0.285	0.070		
Gini parents 2000 perturbation 1			0.383	0.121
Gini parets 2000 perturbation 2			0.290	0.073

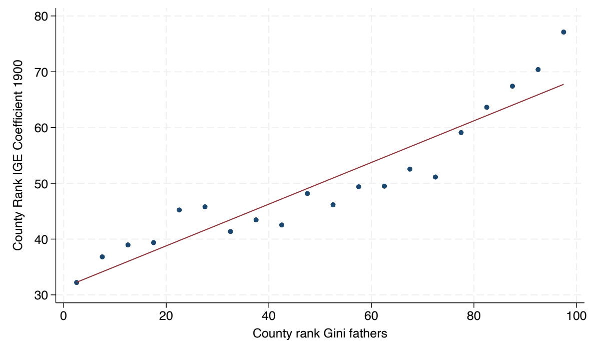
Table A12: Comparison of mean and standard deviation for different Gini measures
Rows 1 and 2 show the mean and standard deviations for the parental Gini coefficients for the 2000 and 1920-1940 data. Columns 3 and 4 show the average mean and standard deviation for two perturbations of the 2000 parental Gini coefficient, as described in the text.

	(1) Regression coefficient Data	(2) Mean regression coefficient Across 1,000 error draws
Dynamic GGC	0.120	
Perturbation 1		0.059
Perturbation 2		0.059

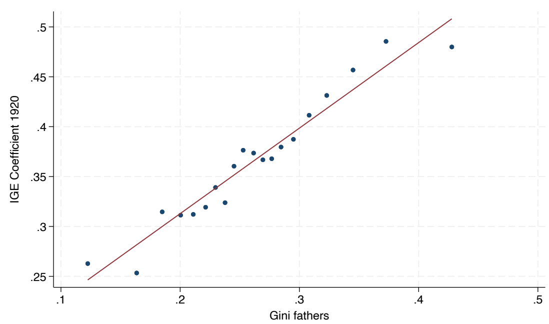
Table A13: Perturbed dynamic GGC coefficients
Comparison of the actual dynamic GGC coefficient for 1940-2000 (row 1) with the average dynamic GGC coefficients over 1,000 draws resulting from perturbations 1 and 2, as described in the Appendix A.



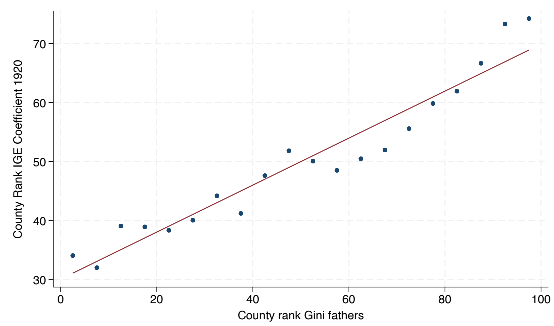
(a) Levels. IGE vs Gini, 1900



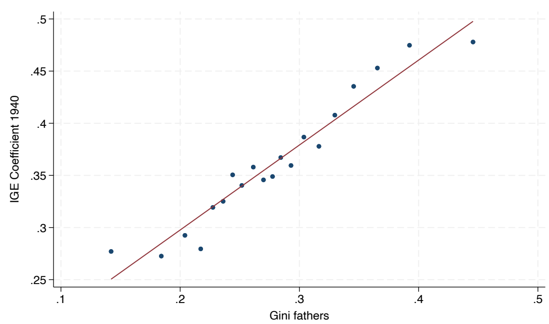
(b) County Ranks. IGE vs Gini, 1900



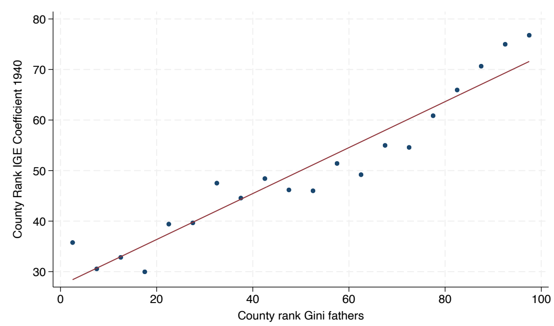
(c) Levels. IGE vs Gini, 1920



(d) County Ranks. IGE vs Gini, 1920



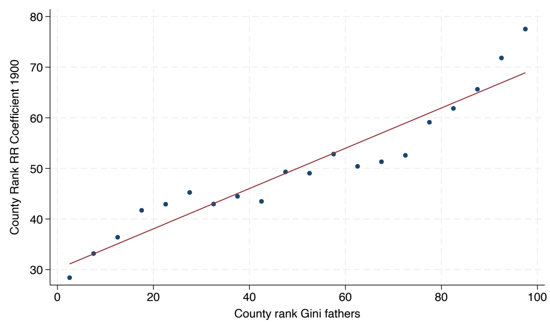
(e) Levels. IGE vs Gini, 1940



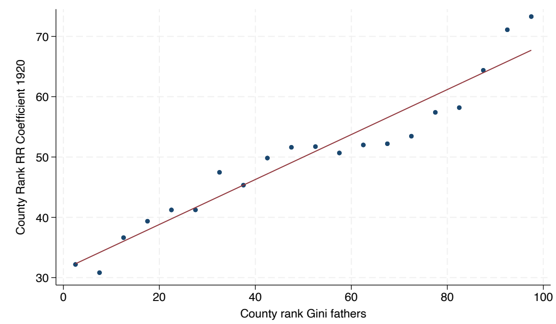
(f) County Ranks. IGE vs Gini, 1940

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.

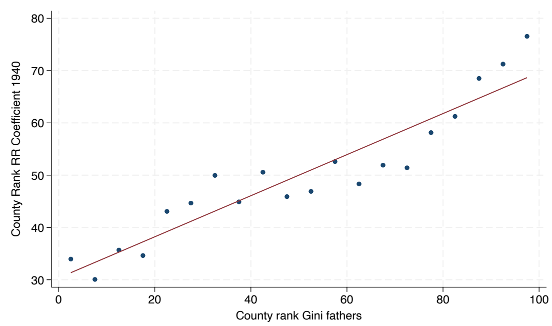
Figure A1: IGE versus Gini, Levels and County Ranks.



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



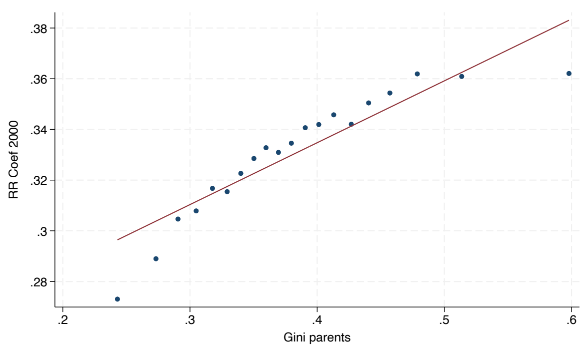
(b) County Ranks. r-r vs Gini, 1920



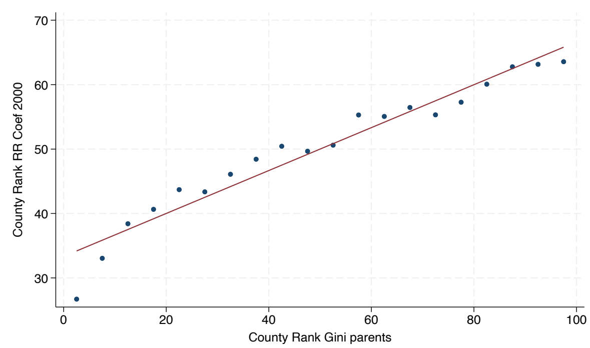
(c) County Ranks. r-r vs Gini, 1940

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.



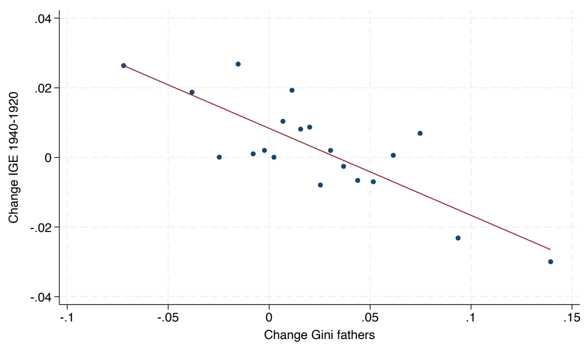
(a) Levels. r-r vs Gini, 2011



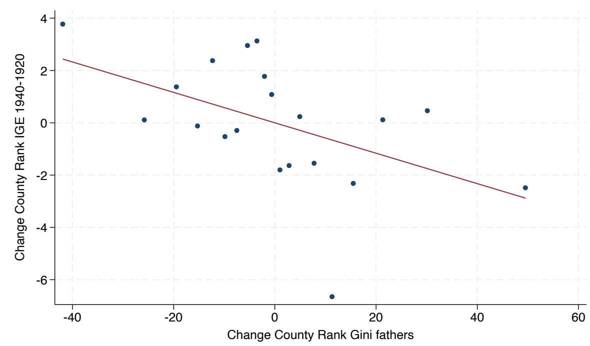
(b) County Ranks. r-r vs Gini, 2011

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. (2014a). 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.

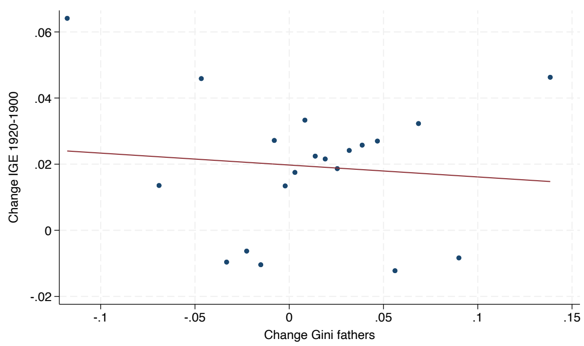
Figure A3: 2011. r-r versus Gini, Levels and County Ranks.



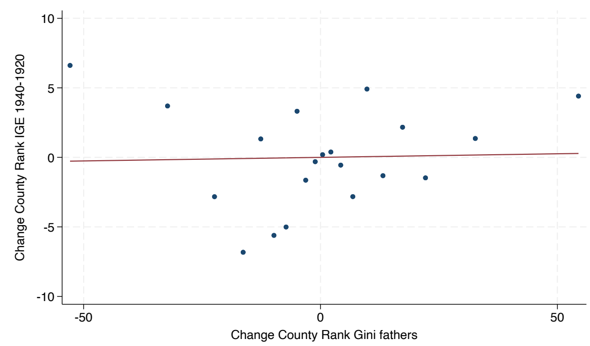
(a) Levels. ΔIGE vs ΔGini, 1920-1940



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



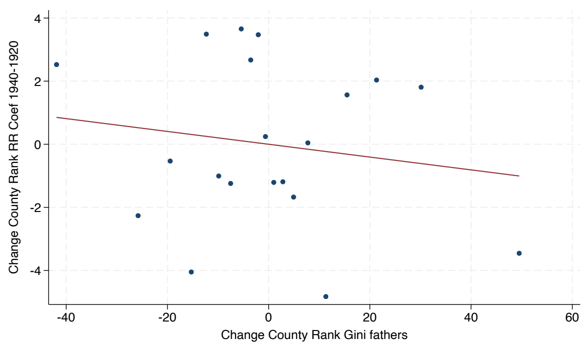
(c) Levels. ΔIGE vs ΔGini, 1900-1920

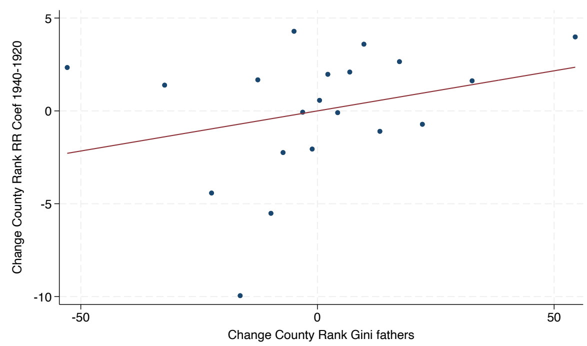


(d) County Ranks. ΔIGE vs ΔGini, 1900-1920

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 A4: Dynamic GGC, IGE. Levels and County Ranks.

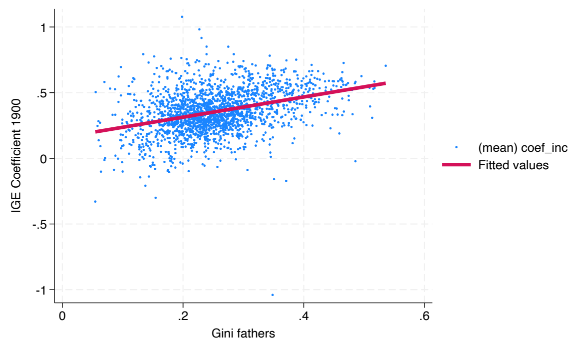




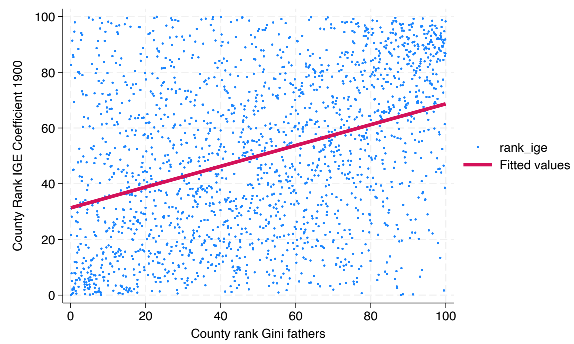
(a) County Ranks. Δr-r vs ΔGini, 1920-1940 **(b)** County Ranks. Δr-r vs ΔGini, 1900-1920

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.

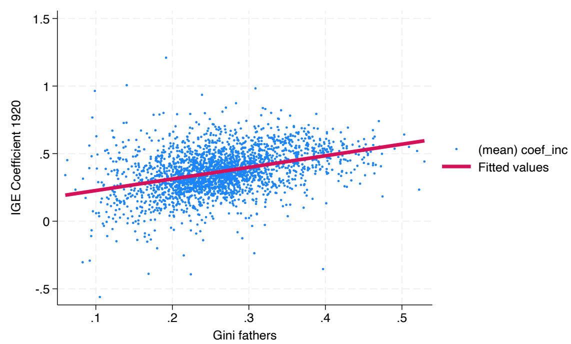
Figure A5: Dynamic GGC, r-r. County Ranks.



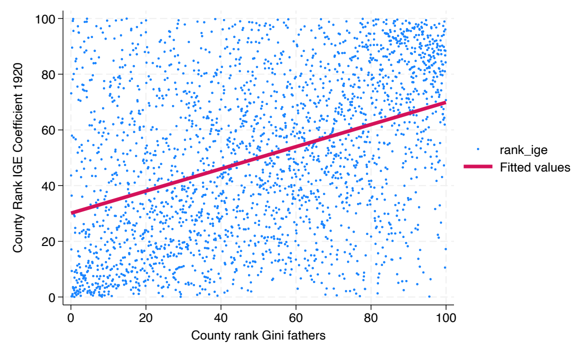
(a) Levels. IGE vs Gini, 1900



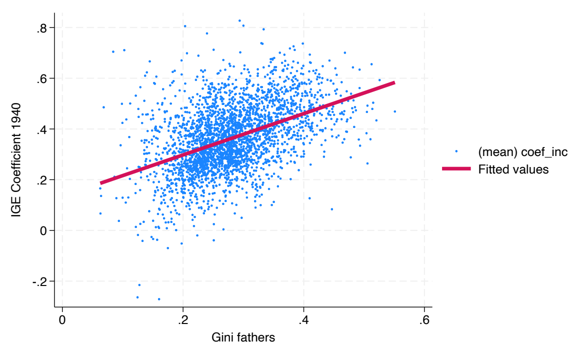
(b) County Ranks. IGE vs Gini, 1900



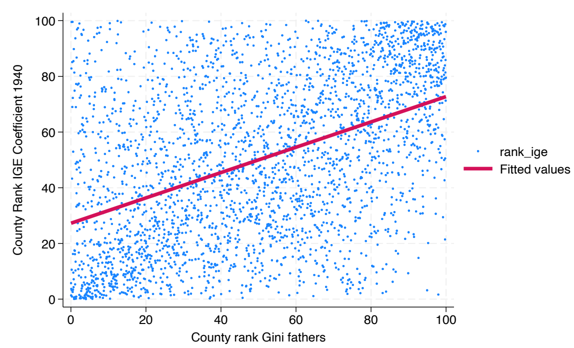
(c) Levels. IGE vs Gini, 1920



(d) County Ranks. IGE vs Gini, 1920

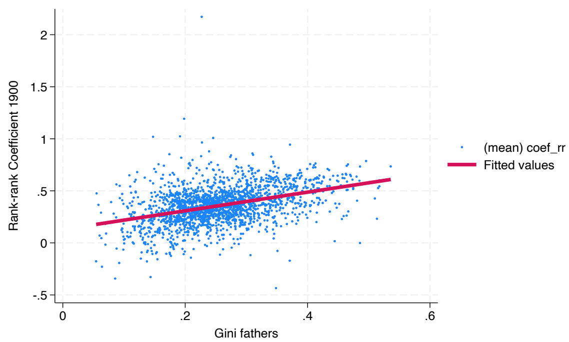


(e) Levels. IGE vs Gini, 1940

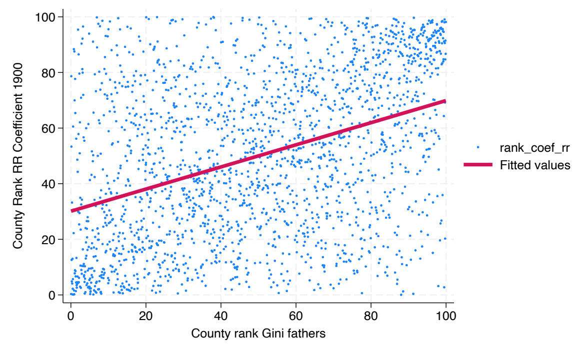


(f) County Ranks. IGE vs Gini, 1940

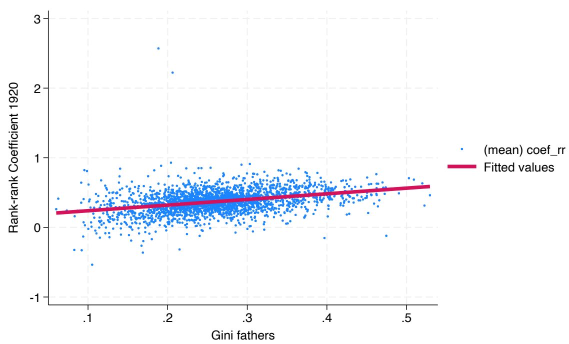
Figure A6: IGE versus Gini, Levels and County Ranks.



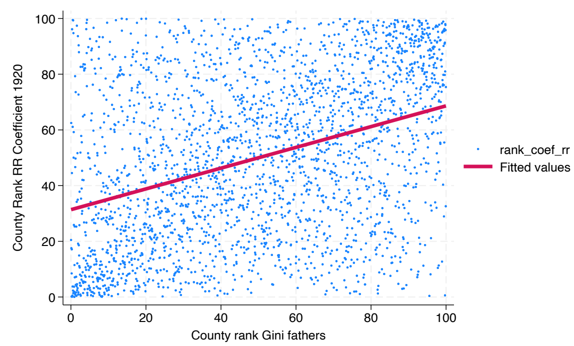
(a) Levels. r-r vs Gini, 1900



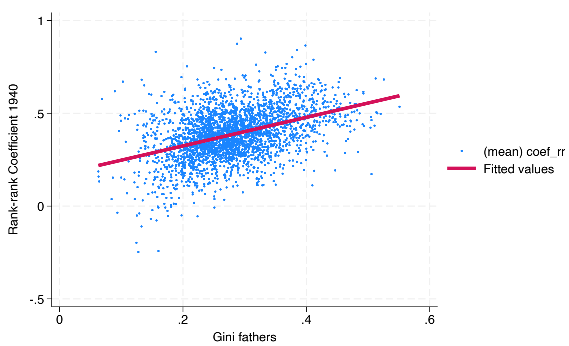
(b) County Ranks. r-r vs Gini, 1900



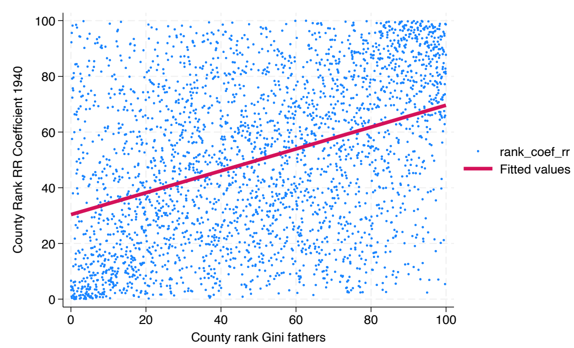
(c) Levels. r-r vs Gini, 1920



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

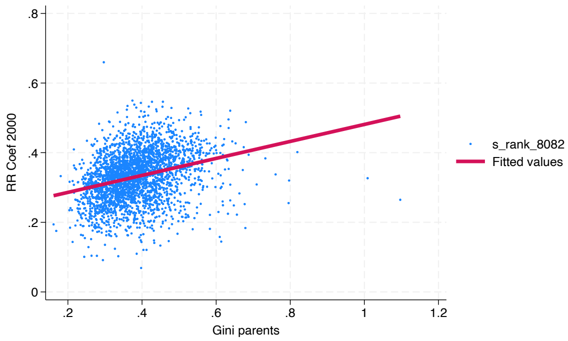


(e) Levels. r-r vs Gini, 1940

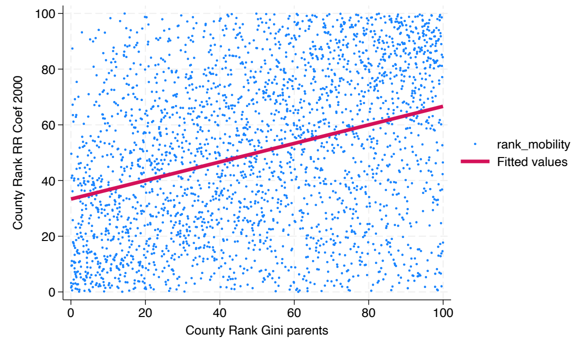


(f) County Ranks. r-r vs Gini, 1940

Figure A7: r-r versus Gini, Levels and County Ranks.

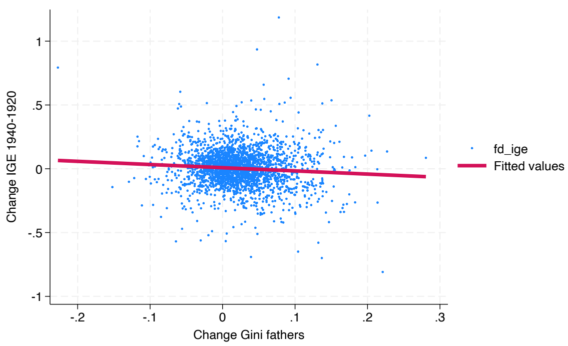


(a) Levels. r-r vs Gini, 2011

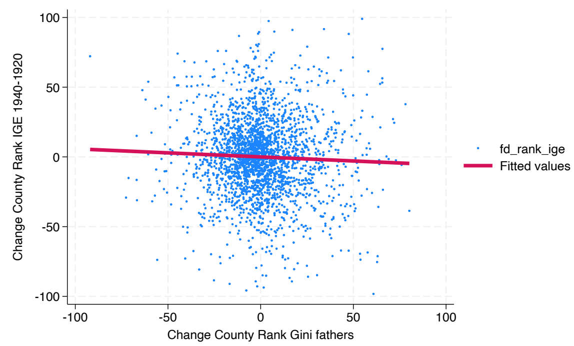


(b) County Ranks. r-r vs Gini, 2011

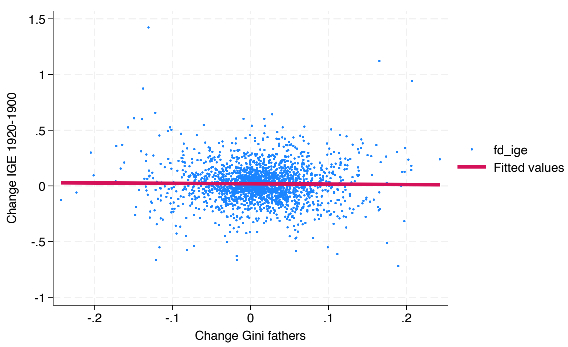
Figure A8: 2011. r-r versus Gini, Levels and County Ranks.



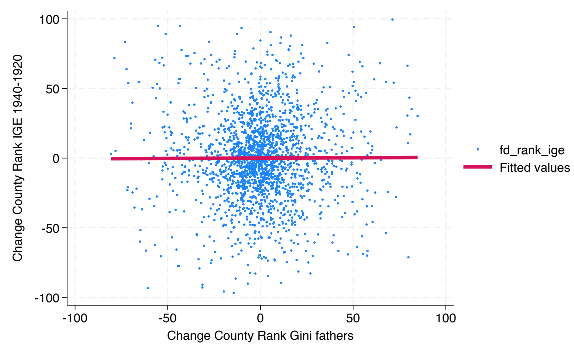
(a) Levels. ΔIGE vs ΔGini, 1920-1940



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

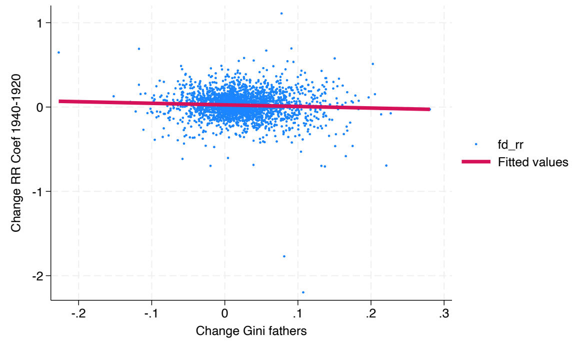


(c) Levels. ΔIGE vs ΔGini, 1900-1920

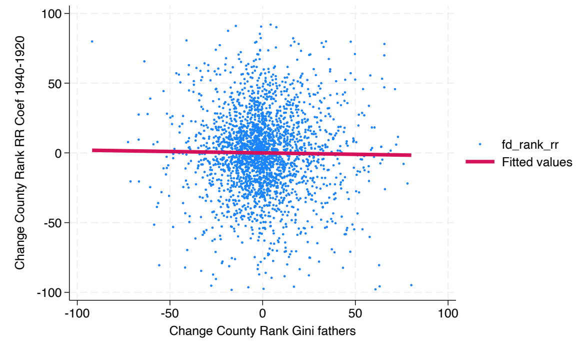


(d) County Ranks. ΔIGE vs ΔGini, 1900-1920

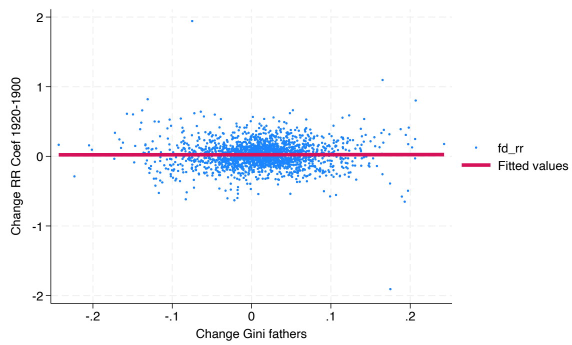
Figure A9: Dynamic GGC, IGE. Levels and County Ranks.



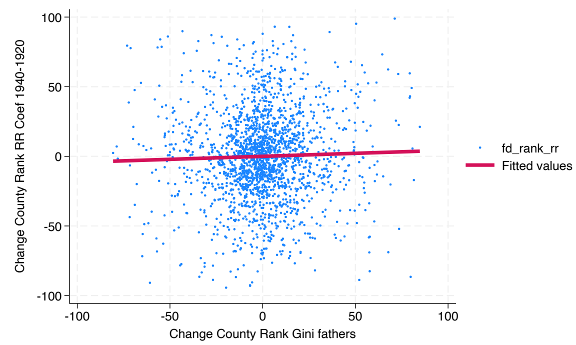
(a) Levels. Δr-r vs ΔGini, 1920-1940



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

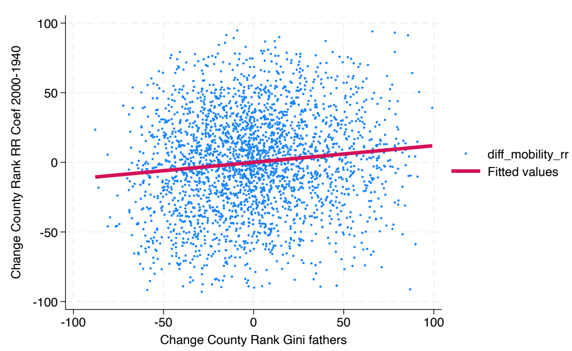


(c) Levels. Δr-r vs ΔGini, 1900-1920

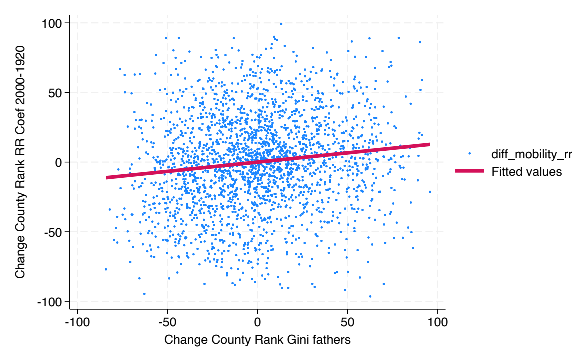


(d) County Ranks. Δr-r vs ΔGini, 1900-1920

Figure A10: Dynamic GGC, r-r. Levels and County Ranks.

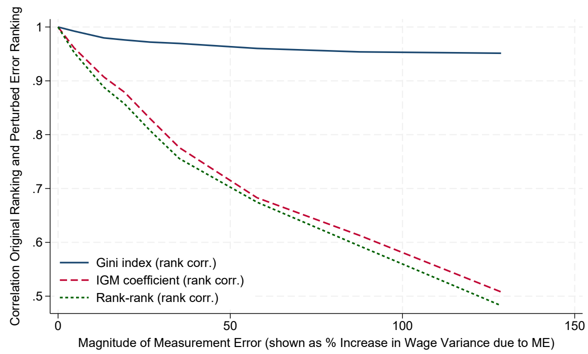


(a) County Ranks. Δr-r vs ΔGini, 1940-2011

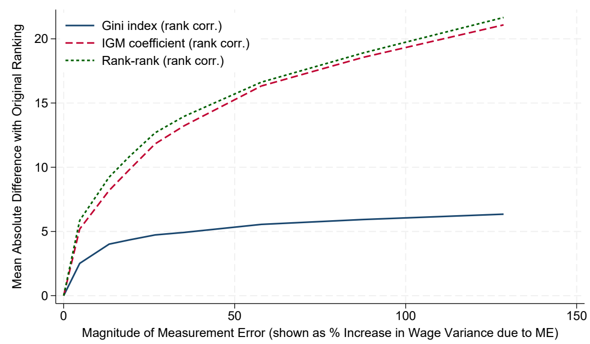


(b) County Ranks. Δr-r vs ΔGini, 1920-2011

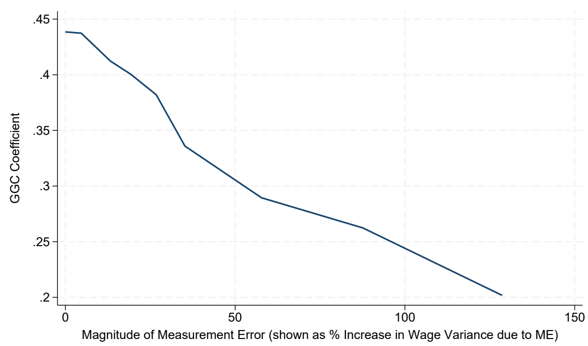
Figure A11: Long Run Dynamic GGC, r-r. Levels and County Ranks.



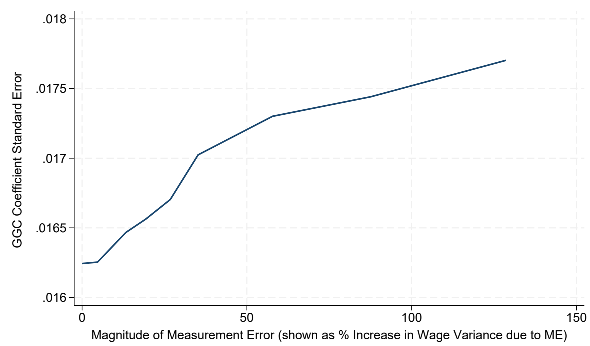
(a) Correlation Original vs. Perturbed Ranking



(b) Mean Absolute Differences in Ranking



(c) GGC slope



(d) GGC standard error

Each panel illustrates the effect of increasing measurement error on key cross-county summary statistics. The x-axis shows the magnitude of measurement error, expressed as the percent increase in the variance of wages (relative to the original distribution) due to the added error. For the analysis sample of sons observed in 1940 and their fathers, both father's and son's log-wages are perturbed by adding independent, normally distributed noise—where the variance of the noise is proportional to the within-county wage variance for each generation—and then exponentiating, so that $\text{wage}_{\text{error}} = \exp\left(\log(\text{wage}) + \varepsilon\right)$ with $\varepsilon \sim N\left(0,\, \sigma^2_{\text{county}}\right)$ drawn independently for each individual and generation.

Panel (a) plots the correlation between original county rankings and rankings obtained after introducing measurement error, for three measures: the Gini index, the IGM regression coefficient, and the rank-rank regression coefficient. Panel (b) shows the mean absolute difference between original and perturbed rankings for the same three measures. Panel (c) displays the estimated coefficient from the cross-sectional Great Gatsby Curve (GGC) regression—linking county-ranking in Gini and ranking in IGM—at each error level. Panel (d) presents the corresponding standard error for the GGC coefficient.

Figure A12: Robustness of Rankings and GGC to Measurement Error