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Does inequality reduce mobility?

The Great Gatsby Curve and its mechanisms

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The Great Gatsby Curve and its mechanisms

by

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Abstract

A body of evidence has emerged in the literature on intergenerational mobility documenting that countries with large income differences also have less intergenerational mobility: a relationship known as the Great Gatsby Curve. In this paper, I estimate the Great Gatsby Curve within Sweden exploiting both cross-sectional and longitudinal variation. I find that men who grew up in regions or periods with high levels of income inequality experienced less intergenerational mobility as adults, thereby confirming the existence of a Great Gatsby Curve in Sweden. I also present new evidence on the underlying mechanisms of the Great Gatsby Curve. By decomposing intergenerational mobility into separate transmission channels, I find that the mediating effects that educational attainment and cognitive and non-cognitive skills have on the persistence of socioeconomic status across generations drive the Great Gatsby Curve.

Keywords: Intergenerational mobility, equality of opportunity, inequality. **JEL-codes:** D31, I24, J62, R0.

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1 Introduction

Income inequality has been increasing in OECD countries since the 1980's (OECD, 2011). In the wake of this development, concerns have been raised about the adverse effects of inequality on socioeconomic mobility, as expressed by Alan B. Krueger in a speech to the Center for American Progress.

> *"Support for equality of opportunity should be a nonpartisan issue. It is hard not to bemoan the fact that because of rising inequality the happenstance of having been born to poor parents makes it harder to climb the ladder of economic success. There is a cost to the economy and society if children from low income families do not have anything close to the opportunities to develop and use their talents as the more fortunate kin from better off families who can attend better schools, receive college prep tutoring, and draw on a network of family connections in the job market."* (Krueger, 2012)

Krueger, building on previous work by Corak (2006), presented a scatter plot of the relationship between inequality and the intergenerational elasticity of income (IGE) across countries. The data points clustered along an upward sloping line indicating that unequal societies experience less socioeconomic mobility – a relationship he called the Great Gatsby Curve.

An early reference on the relationship between inequality and mobility is Björklund and Jäntti (1997) who compares Sweden and the United States.[1] Since then, a number of studies have corroborated the finding that countries with high levels of inequality experience less intergenerational mobility (Corak, 2006; Andrews and Leigh, 2009; Ermisch et al., 2012; Corak, 2013; Blanden, 2013; Jerrim and Macmillan, 2015). However, does the Great Gatsby Curve also exist across regions within the same country?

Two main sources of heterogeneity suggest that estimates across regions within the same country can differ from cross-country estimates. First, the institutions and conditions that determine the transmission of socioeconomic status from one generation to the next - such as labor market institutions, taxation policies, social security, access to education and health care, marital sorting, segregation, cultural norms, etc. - undoubtedly varies more across countries than within countries. Second, differences in income definitions, sample frames, and estimation methods complicate the juxtaposition of mobility and inequality across countries. By studying the relationship between inequality and mobility

[1] The paper by Björklund and Jäntti (1997) was preceded by empirical work in the sociological literature (see Erikson and Goldthorpe (1992)).

across regional units within the same country, and thereby relying on consistent measurements across regions with a high degree of institutional and cultural homogeneity, these difficulties are greatly mitigated.

To my knowledge, the first study to estimate the Great Gatsby Curve across regions within the same country is Chetty et al. (2014), who estimate mobility and inequality across commuting zones in the United States. The Great Gatsby Curve has also been estimated across provinces in China by Fan et al. (2015) and across provinces in Italy by Güell et al. (2018). Although the within-country comparisons of China and the United States certainly improve the consistency of measurement units and estimation methods, they are nevertheless countries with large cultural and institutional heterogeneity at the regional level.[2] Furthermore, though Güell et al. (2018) estimate a Great Gatsby in Italy, which is a more homogeneous country than China and the United States, their analysis is restricted by the limitations of their data. Income is only observed from tax declarations in one year, which means that they ingeniously must rely on the informational content of the surnames on the forms to estimate a mobility metric. However, since inequality is observed in the same year as mobility, what they estimate is the *instantaneous* relationship between mobility and inequality, which is not the same as estimating the relationship between inequality during childhood and its effect on the *subsequent* intergenerational transmission of socioeconomic status.

The purpose of this paper is therefore twofold. First, to investigate whether the Great Gatsby Curve exists across regions in a country of substantial institutional and cultural homogeneity using administrative registry data that enables consistent measurements over time. To this end, I estimate the relationship between childhood inequality (i.e. the average regional inequality level during childhood) and subsequent intergenerational mobility across 125 commuting zones (CZ) and 20 cohorts in Sweden, exploiting both cross-sectional and longitudinal variation. The second aim of the paper is to investigate the mechanisms of the Great Gatsby Curve. To do this, I decompose intergenerational mobility into four orthogonal transmission channels and investigate their association with childhood inequality. The transmission channels are; educational attainment, cognitive skills, non-cognitive skills, and a residual effect that captures the remaining transmission of socioeconomic status across generations, such as the direct effect of parental income and the effect of social networks, hereditary traits, etc.

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[2] In their study of regional differences in intergenerational mobility, Chetty et al. (2014) describes the United States as “a collection of societies”.

Intergenerational mobility can be estimated in many different ways but in this study I focus on the intergenerational rank persistence (IRP), generally obtained as slope coefficients from bivariate regressions of children's income rank on the income rank of their parents.[3] To obtain robust estimates of the IRP, each individual is assigned an income rank based on their average annual income among all males born in the same year at the national level (Nybom and Stuhler, 2016). To measure the level of inequality that each individual is exposed to prior to labor market entry, I define childhood inequality as the average annual regional Gini coefficients between ages -1 and 18. I then regress intergenerational rank persistence on childhood inequality at the CZ by cohort level to estimate the Great Gatsby Curve.

I find that children who were exposed to higher levels of inequality during childhood experienced less intergenerational mobility as adults, and that this is true whether comparing children who grew up in the same commuting zones but were born in different years, or whether comparing children who were born in the same year but grew up in different commuting zones. A one standard deviation increase in childhood inequality is associated with a 0.019 increase in IRP, which corresponds to a 7 percent increase relative to the average rank persistence at 0.26. Taking these estimates at face value, average childhood inequality in Sweden would have to increase by three standard deviations for the persistence of income ranks across generations to reach the same level as in the United States (Chetty et al., 2014).[4] I also find that inequality has a stronger association with mobility at the lower end of the inequality distribution, and that the relationship between inequality and mobility is strongest during the first years of childhood (age -1 to 2).

Turning to the mechanisms, I find that the mediating effect of children's educational attainment and development of cognitive and non-cognitive skills account for about 53 percent of the intergenerational rank persistence. The remaining persistence is accounted for by the residual effect, but in spite of it accounting for almost half of the total persistence, it is completely uncorrelated with childhood inequality. In contrast, all three mediation effects are positively associated with childhood inequality: a one standard deviation increase in childhood inequality is associated with a 0.22 standard deviation increase in the mediation effect of children's educational attainment on the intergenerational

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[3] I refer interchangeably to "mobility" and "persistence" in the paper, where the former is understood to have an inverse relationship to the latter.

[4] Chetty et al. (2014) estimates the U.S. rank persistence to 0.317 for sons born 1980-1982 (see the second column of Table 1).

rank persistence, and a 0.26 and 0.28 standard deviation increase in the mediation effect of children's cognitive and non-cognitive skills. Hence, the results suggest that the Great Gatsby Curve is driven by the mediating effect that children's educational attainment and cognitive and non-cognitive skills has on intergenerational mobility. Another way of putting it is that children who grew up in regions or periods with high levels of income inequality experienced less socioeconomic mobility because their educational attainment and cognitive and non-cognitive skills were more strongly associated with their parents income.

Thus, this paper makes two contributions to the existing literature on inequality and mobility. First, by estimating the Great Gatsby Curve across regions with an exceptionally high level of institutional and cultural homogeneity, using both spatial and temporal variation. I combine administrative registers to create an income panel spanning 53 years with information on residency and parent-child links that allows for consistent estimates in consecutive generations for 20 cohorts: a feat unparalleled in previous studies of the relationship between mobility and inequality. The second contribution is that I study the mechanisms of the Great Gatsby Curve. By decomposing the intergenerational rank persistence into separate channels using data on the children's educational achievement and cognitive and non-cognitive skills, I am able to investigate how the different mechanisms that determine the transmission of socioeconomic status across generations respond to changes in inequality.

The paper proceeds as follows. I present a theoretical framework for the transmission of income across generations in section 2. Section 3 describes the estimation, while the data and sample selection is covered in Section 4. Estimates of the Great Gatsby Curve is presented in section 5, and section 6 presents results on the underlying mechanisms. Robustness checks are presented in section 7, and section 8 concludes.

2 Theoretical framework

There are strong theoretical underpinnings for the Great Gatsby Curve that dates back to seminal papers by Gary Becker and Nigel Tomes (1979; 1986). They establish a link between cross-sectional inequality for the parent generation and the subsequent intergenerational persistence of income by formulating a model where the utility optimizing behavior of families means that parents invest more in the human capital of their children when the returns to those investments are high; i.e. when inequality is high. Since rich parents can afford to invest more in the human capital of their children, increasing levels of inequality in the Becker-

Tomes model implies that the intergenerational persistence of income will increase.

Solon (2004) extends the Becker-Tomes model in a way that rationalizes the intergenerational elasticity of income and allows for an analysis of the impact of public investments in children's human capital. In Solon's model, inequality is decreasing in the progressiveness of public investments in children's human capital, and increasing in the heritability of biological endowments, the returns to human capital investments, and the earnings return to human capital. Meanwhile, mobility is increasing in the progressiveness of public investments and decreasing in the heritability of biological endowments, the returns to human capital investments, and the earnings return to human capital. Hence, that model also predicts a negative correlation between inequality and mobility.[5]

In this section, I present a theoretical framework that closely follows prior work by Rothstein (2017) and Blanden et al. (2007), to fix ideas about how income is transmitted across generations. Admittedly, this theoretical framework abstracts from much of the theoretical richness in the Becker-Tomes model and its extensions.

2.1 A framework for the transmission of income across generations

Let regions be indexed by *r* and cohorts by *t*. Then suppose that an individual's lifetime income, *y*, is determined by separate processes in two periods indexed by subscripts *1* and *2*. In the first period, a vector of income-generating skills, $\boldsymbol{a}_{1rt}$, is acquired prior to labor market entry as a function of parental lifetime income, y^p:

$$\boldsymbol{a}_{1rt} = \boldsymbol{g}_{1rt}(y^p)$$

Here, $\boldsymbol{g}_{1rt}(y^p)$ reflects the institutions and conditions that govern the transmission of parental income into children's production of income-generating skills in each region *r* for each cohort *t*. Examples of such institutions and conditions are social security, crime rates, segregation, unemployment, the education system, access to healthcare, and so on. In the next period, income y_{rt}

[5] The impact of public investments on intergenerational mobility and cross-sectional inequality is further elaborated upon in a recent model by Becker et al. (2018). In that model, parental human capital and parental investments are complementary, thereby incorporating the very plausible notion that parents with high levels of human capital are better at investing in their children's human capital. Their model thus predicts that the impact of public investments on intergenerational mobility will depend upon if those investments substitute or complement parental investments.

is determined by the acquired skills in the previous period and parental income, again mediated by the regional institutions and conditions at the time:

$$y_{rt} = f_{2rt}(\boldsymbol{a}_{1rt}, y^p)$$

The reduced form relationship of income across generations can then be expressed as:

$$y_{rt} = f_{2rt}(\boldsymbol{g}_{1rt}(y^p), y^p)$$

Hence, the effect of parental income on children's income, i.e. the intergenerational persistence of income, is defined as:

$$\frac{dy_{rt}}{d\, y^p} = \frac{\partial f_{2rt}}{\partial \boldsymbol{g}_{1rt}} * \frac{\partial \boldsymbol{g}_{1rt}}{\partial\, y^p} + \frac{\partial f_{2rt}}{\partial\, y^p}$$

The first term captures the effect of parental income on children's development of skills as mediated by the regional institutions and conditions at the time, multiplied by the effect of skills on income (again as mediated by the regional institutions and conditions at the time). A large effect of this term suggests that parental income mainly affects children's income by investments in their income-generating skills. The second term captures the conditional effect of parental income on children's income, and a large effect of this term implies that parental income either has a large direct effect on children's income, or that parental income affects children's income through channels not captured by income-generating skills. Examples of such channels could be access to social networks that facilitate success in the labor market, or hereditary traits such as good looks and skin-tone.

2.2 Transmission mechanisms and the standard measure of intergenerational income persistence

To see how the transmission mechanisms derived in this framework relate to the standard measure of intergenerational income persistence, I will assume for the moment that skill is uni-dimensional and that $\boldsymbol{g}_{1rt}$ and f_{2rt} are linear functions with errors that are uncorrelated with parental income:

$$a_{1rt} = g_{1rt}(y^p) = \kappa_{1rt} + \varphi_{1rt} + \mu_{1rt}$$

$$y_{rt} = f_{2rt}(a_{1rt}, y^p) = \kappa_{2rt} + \rho_{2rt}a_{1rt} + \delta_{rt}y^p + \mu_{2rt}$$

Now the reduced form relationship of income across generations can be expressed as:

$$y_{rt} = \kappa_{2rt} + \rho_{2rt}(\kappa_{1rt} + \varphi_{1rt} + \mu_{1rt}) + \delta_{rt} y^p + \mu_{2rt}$$

$$= \kappa_{2rt} + \rho_{2rt}\mu_{1rt} + \rho_{2rt}\kappa_{1rt} + (\rho_{2rt}\varphi_{1rt} + \delta_{rt})y^p + \mu_{2rt}$$

Moreover, the intergenerational persistence of income can be expressed as:

$$\frac{dy_{rt}}{d\, y^p} = \rho_{2rt}\varphi_{1rt} + \delta_{rt}$$

The returns to the uni-dimensional income-generating skill is captured by ρ_{2rt} and the effect of parental income on the production of the skill is captured by φ_{1rt}, analogous to $\frac{\partial f_{2rt}}{\partial g_{1rt}} * \frac{\partial g_{1rt}}{\partial\, y^p}$ while δ_{rt} reflects the conditional effect of parental income on children's income analogous to $\frac{\partial f_{2rt}}{\partial\, y^p}$.

Now, the standard measure of intergenerational income persistence is generally obtained as the OLS estimate of the slope coefficient from regressing parental income on children's income:

$$y = \alpha + \beta\ \ y^p + \varepsilon$$

Assuming a sample of *n* individuals and their parents, the probability limit of the OLS estimator of β as $n \to \infty$ is:

$$plim\hat{\beta} = \frac{Cov(y,\, y^p)}{V(\, y^p)} = \ \beta + \frac{Cov(\varepsilon,\, y^p)}{V(\, y^p)}$$

Here, β is the causal effect of parental income on children's income and the last term, $\frac{Cov(\varepsilon,\, y^p)}{V(\, y^p)}$, accounts for all other channels that causes income to persist across generations including genetic endowments, social networks and so on. Therefore, the standard measure of intergenerational income persistence, $\hat{\beta}$, should be understood as a *descriptive* measure that incorporates the combined influence of all variables that are correlated with y^p and y in addition to any causal effect.

The standard measure of intergenerational income persistence can be expressed in terms of the framework outlined in this section as:

$$y_{rt} = \alpha_{1rt} + \beta_{rt}\ \ y^p + \varepsilon^*_{rt}$$

$$\varepsilon^*_{rt} = \rho_{2rt} a_{1rt} + \mu_{2rt}$$

The probability limit of the OLS estimator of β_{rt} is then:

$$plim\widehat{\beta_{rt}} = \frac{Cov(\alpha_{1rt} + \beta_{rt}\ \ y^p + \varepsilon^*_{rt},\, y^p)}{V(\, y^p)}$$

$$= \beta_{rt} + \frac{Cov(\rho_{2rt}(\kappa_{1rt} + \varphi_{1rt} + \mu_{1rt}) + \mu_{2rt}, y^p)}{V(y^p)}$$

$$= \beta_{rt} + \rho_{2rt}\varphi_{1rt}$$

Recognizing that $\beta_{rt} = \delta_{rt}$ assuming the model is correctly specified, we can see that the sum of the transmission coefficients is equal to the standard measure of intergenerational income persistence, $\widehat{\beta_{rt}}$, which means that the transmission coefficients decompose $\widehat{\beta_{rt}}$ into orthogonal components that goes through the development of (and returns to) the income-generating vector $\boldsymbol{a}_{1rt}$, plus the conditional effect of parental income given the mediation of the transmission mechanisms captured by δ_{rt}.

3 Estimation

In this section, I discuss some conceptual differences between common measures of intergenerational mobility before I turn to the estimation of the Great Gatsby Curve. I then describe the decomposition of intergenerational mobility into separate transmission channels and how they are estimated.

3.1 The Great Gatsby Curve

The Great Gatsby Curve is estimated in two steps; I first estimate intergenerational mobility and calculate childhood inequality (by averaging annual Ginicoefficients) at the CZ by cohort level, and then regress the mobility estimates onto the childhood inequality measures. However, as pointed out by Chetty et al. (2014), measuring intergenerational income persistence amounts to choosing one out of several statistics that characterize the joint distribution of parent and child income. The most common statistic in the empirical literature has been the intergenerational elasticity of income (IGE), obtained as OLS estimate of the slope coefficient in a regression of children's log (lifetime) income on parental log (lifetime) income:

$$ln(y) = \alpha + \beta\, ln(y^p) + \varepsilon$$

A feature of the IGE is that it incorporates changes in inequality across generations. To see this, recall that the Pearson correlation coefficient is obtained by dividing the covariance between two variables with the product of their standard deviations. Hence, the IGE is related to the correlation coefficient through the ratio of the standard deviations of the marginal income distributions:

$$\beta = \frac{Cov(y, y^p)}{V(y^p)} = \beta + \frac{Cov(\varepsilon, y^p)}{SD(y^p)SD(y)}\left(\frac{SD(y)}{SD(y^p)}\right) = \rho\left(\frac{SD(y)}{SD(y^p)}\right)$$

Here ρ is the Pearson correlation coefficient and β is the IGE. Therefore, increasing inequality across generations will increase the IGE relative to the correlation. However, the intergenerational rank persistence (IRP) suggested by Dahl and DeLeire (2008) does not depend on the marginal income distributions since the ranking of incomes transforms the marginal distributions of parent and child income into uniform distributions.[6] This begs the question, which measure of intergenerational mobility is preferable?

Since the IGE has been shown to be more susceptible to measurement error and life cycle bias (Nybom and Stuhler, 2016), both of which are matters of concern in this study, I will use the IRP to estimate intergenerational mobility.[7] So, from now on let y_{irt} denote the income rank of individual i born in year t who grew up in commuting zone r, and let y_{irt}^{p} denote the parental income rank. The intergenerational rank persistence is then obtained as the OLS estimate of the slope coefficient in a regression of children's income rank on parental income rank:

$$y_{irt} = \alpha_{rt} + \beta_{rt}\, y_{irt}^{p} + \varepsilon_{irt}$$

Here β_{rt} measures the expected change in children's income rank following a one-percentile increase in parental income rank in each commuting zone r for each cohort t. The next step is to regress intergenerational rank persistence on childhood inequality denoted by z_{rt}:

$$\beta_{rt} = \alpha + \theta z_{rt} + \varepsilon_{rt}$$

The slope of the Great Gatsby Curve is captured by θ which measures the expected change in intergenerational rank persistence following a one-unit increase in childhood inequality.

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[6] When the ranking is done at the national level, the marginal distributions of income ranks at the CZ level will generally deviate slightly from the uniform distribution.

[7] For example, Haider and Solon (2006) showed that income early in life produces a downward-inconsistent estimate of lifetime income, and that income late in life produces an upward-inconsistent estimate (see Böhlmark and Lindquist (2006) for an application to Swedish data). Therefore, the most common way to deal with measurement error and life cycle bias has been to average income over multiple years at points in life when the income trajectories do a good job of approximating lifetime income. The optimal age to measure income seems to be around 32 to 40 years of age for Swedish males (Böhlmark and Lindquist, 2006).

3.2 Mediation effects

To estimate the amount of income persistence that is channeled through educational attainment, cognitive skills, and non-cognitive skills, I first estimate their association with parental income ranks from bivariate regressions (separately for each cohort in each CZ):[8]

$$\begin{aligned} e_{irt} &= \psi_{1rt} + \varphi_{1rt} y_i^p + v_{1irt} \\ c_{irt} &= \psi_{2rt} + \varphi_{2rt} y_i^p + v_{2irt} \\ n_{irt} &= \psi_{3rt} + \varphi_{3rt} y_i^p + v_{3irt} \end{aligned}$$

Here e_{irt}, c_{irt} and n_{irt} is the educational attainment, cognitive skills and non-cognitive skills of individual *i*, raised in commuting zone *r* in year *t*, and y_i^p is the parental income rank. Hence, these estimation equations are analogous to estimating $\left(\frac{\partial \boldsymbol{g}_{1rt}}{\partial\, y^p}\right)$ in Section 2.1.

The next step is to estimate conditional returns in a regression that includes the mediating variables as well as parental income rank, which corresponds to estimating $\left(\frac{\partial f_{2rt}}{\partial \boldsymbol{a}_{1rt}}\right)$ and $\left(\frac{\partial f_{2rt}}{\partial\, y^p}\right)$ in Section 2.1:

$$\begin{aligned} y_{irt} &= \gamma_{rt} + \rho_{1rt} e_{irt} + \rho_{2rt} c_{irt} + \rho_{3rt} n_{irt} + \delta_{1rt} y_i^p + v_{irt} \\ &= \gamma_{rt} + (\rho_{1rt}\psi_{1rt} + \rho_{2rt}\psi_{2rt} + \rho_{3rt}\psi_{3rt} + \delta_{1rt}) y_i^p + v_{irt}^* \\ v_{irt}^* &= (\psi_{1rt} + v_{1irt})\rho_1 + (\psi_{2rt} + v_{2irt})\rho_1 + (\psi_{3rt} + v_{3irt})\rho_3 + v_{irt} \end{aligned}$$

Where y_{irt} is the income rank of individual *i*. The intergenerational rank persistence is then given by:

$$\frac{dy_{irt}}{dy_i^p} = \rho_{1rt}\psi_{1rt} + \rho_{2rt}\psi_{2rt} + \rho_{3rt}\psi_{3rt} + \delta_{1rt}$$

The mediation effect of children's educational attainment is the product of the conditional returns to education and the effect of parental income rank on education: $\rho_{1rt}\varphi_{1rt}$. The mediation effects of cognitive and non-cognitive skills are defined analogously as $\rho_{2rt}\varphi_{2rt}$ and $\rho_{3rt}\varphi_{3rt}$, while δ_{1rt} is the ”residual term” that captures the remaining association of income across generations after the mediating variables have been controlled for. However, to estimate the transmission coefficients without bias the errors from estimating the association

[8] This section also closely follows prior work by Blanden et al. (2007) and Rothstein (2017).

between parental income ranks must be uncorrelated with the errors from estimating the conditional returns, i.e. that:[9]

$$Cov(v_{irt}, v_{1irt}) = Cov(v_{irt}, v_{2irt}) = Cov(v_{irt}, v_{3irt}) = 0$$

To get an idea of what kind of bias that might be present in the estimates, consider the situation where an omitted variable x is positively correlated with children's education and income. In this situation, ρ_{1rt} will be biased upwards and δ_{1rt} will be biased downwards, but only to the extent that x is correlated with education and income *conditional* on cognitive skills, non-cognitive skills and parental income. Hence, the scope for bias due to omitted variables is fairly limited. Bias will also arise if variables are measured with error. In some sense, this is unavoidable when using a ratio scale index to measure multi-dimensional variables like cognitive and non-cognitive skills. Measurement error will bias the estimates of ρ_{1rt}, ρ_{2rt}, and ρ_{3rt} towards zero and consequently overestimate δ_{1rt}. In conclusion, bias due to omitted variables and bias due to measurement error will affect the estimates in opposite directions, and therefore cancel out to some extent.

As previously mentioned, δ_{1rt} captures the association that remain between parent's and children's income ranks when the mediating variables have been accounted for, and I think it is worthwhile to elaborate on what those remaining channels are. Jerrim and Macmillan (2015), while conducting a similar decomposition exercise for the effect of parental education on children's earnings, propose three different channels. The first operates via financial resources directly by enabling high income families to support their children during labor market entry. This would be important if it takes a long time to find a job that maximizes income over the whole career, or if such jobs include low- or unpaid internships. The second channel operates via social networks. Parents with higher income might have more valuable labor market connections that facilitate the labor market success of their children regardless of their children's educational attainment or level of cognitive and non-cognitive skills. Likewise, parents with higher income might also be able to supply their children with a more valuable pool of peers by sending them to select schools or simply living in an area with high socioeconomic status. Finally, the third channel is hereditary endowments such as good looks, height, skin tone, and health endowments, that are unrelated to ability and educational attainment but nevertheless has an effect on labor market success.

[9] The discussion about bias in this section builds on previous work by Adermon et al. (2016).

4 Data

I use several data registers maintained by Statistics Sweden to contruct the sample. The data cover the universe of the Swedish population aged 0-74 years from 1960 until 2012, and their biological parents. All individuals have been linked to the quinquennial national censuses (FoB) 1960-1990; the education register 1985-2012; and the income and tax register (IOT) for a 10 percent sample of the population betweeb 1960-1966 and for the whole population for scattered years between 1968-1984 and all years 1985-2012. As discussed in Jäntti and Jenkins (2015), to measure intergenerational income persistence decisions have to be made about when income is to be measured, what kind of income to include and among whom to measure that income. In this section, I will elaborate on the choices made in this study.

4.1 Sample selection

This study focuses exclusively on the incomes of Swedish men, partly to facilitate comparisons with other studies, but mainly because enlistment into the military has not been mandatory for women, which means that there is no military enlistment data on their cognitive and non-cognitive skills.

To construct the core sample of sons and fathers, I begin by selecting all males born in Sweden between 1961 and 1980 and obtain 1,117,878 sons. I then restrict the sample to sons whose parents are identified in the multi-generation register, which contains parental links to all children born in 1932 or later who were a resident in Sweden at some point from 1961 and onward. Since I study cohorts born between 1961 and 1980, I can connect all sons to their fathers as long as the father is known. I also add the restriction that the fathers must be at least 18 and at most 45 when their son was born. These restrictions reduces the sample by about 4.8 percent. I further restrict the sample to sons whose father was born after 1920 and before 1961 in order to ensure that it is possible to obtain good approximations of their lifetime incomes, which reduces the sample by another 0.9 percent.[10] This leaves me with a core sample of 1,055,163 sons and their fathers.

[10] By dropping all fathers born after 1960 I don't have any cohort overlap between the parent and child generations which means that I won't use the same observation as both a son and a father in the sample. Dropping all fathers born before 1921 means that I observe the incomes of the oldest fathers until 1971 (the year they turn 50) and as a consequence that I potentially observe their income for ten years , but most likely for three years: 1968, 1970 and 1971. Hence, the observation window is similar to that of the youngest sons whose income I also only observe for three years.

I drop all annual incomes below 75 percent of full-time employment on "minimum wage", which in 2012 was about 134,900 SEK (about $19,200). Since Sweden does not have a national minimum wage, I have constructed one based on the results in Skedinger (2005), who shows that the minimum wage is approximately 65 percent of the average wage in each branch of industry, and that this ratio has been more or less constant between 1970 and 2004. I combine those results with changes in the national regulations of the hours of work per week and the number of vacation days per year to calculate an annual minimum income level equal to 75 percent of full-time employment on minimum wage. By imposing the minimum income restriction, I address two problems. The first is the prevalence of cross-border commuting in municipalities along the Norwegian and Finnish border. The commuting means that some workers earn most of their labor market income abroad, which means I cannot observe it. The second problem is the occurrence of small annual labor market incomes that are not representative for an individual's typical income, such as parents exiting the labor market to go on parental leave, or students working during the summer, or individuals that receive a significant share of their income as capital gains. By restricting the sample to fathers and sons with at least three years of observed income above the minimum income threshold, the sample is reduced by another 16 percent. Finally, to ensure that I correctly assign sons to commuting zones, I restrict the sample to sons that lived at least six consecutive years in the same commuting zone between 2 and 12 years of age. About 98 percent of the remaining sons pass this restriction, leaving me with a final sample of 868,557 sons and their fathers.

4.2 Variable definitions and descriptive statistics

Following Chetty et al. (2014), I choose to analyze the Great Gatsby Curve using commuting zones as the geographical unit of analysis. I observe residency in 1960 and 1965 and then annually from 1969. I re-code the residency data to map into the 1977 municipality distribution before aggregating the municipalities into 125 commuting zones.[11]

[11] The Swedish government initiated massive municipality reforms 1952 and 1971. In 1977 the number of municipalities was at an all-time low of 277, compared the 2,532 that existed in 1930 (and the 290 that exists today). By mapping the residency codes into the 1977 municipality distribution I maximize the number of observations in each municipality. The commuting zones were created by Statistics Sweden based on commuting patterns observed in 1985. The explicit purpose of creating the commuting zones was to form local labor market regions suitable for economic analysis (SCB, 2010).

I combine data from the registries to create pre-tax income panels spanning 53 years; from 1960 until 2012. However, I only observe income for 10 percent of the population with a taxable income above one price base amount (roughly $1,600 in 2012 USD) between 19601966. In addition, data from the income and taxation register is only available for the years 1968, 1971, 1973, 1976, 1979 and 1982. After that, the longitudinal database on education, income and occupation (LOUISE) provides annual data from 1985 and onward. There is also income data in the administrative registries from quinquennial censuses (FOB) between 1970 and 1980. All income has been deflated to 2012 SEK and the year associated with each income corresponds to the year in which the income was earned. The income measure includes wage earnings, business income, taxable benefits and some transfers from the social security system such as sick pay and certain parental benefits. Capital earnings, pensions and parental leave are not included. Furthermore, incomes are measured at the individual level since household income explicitly introduces marital sorting as a mechanism through which income is transmitted between generations (Ermisch et al., 2006). I then approximate lifetime labor market incomes for fathers (sons) by averaging annual incomes between 30-50 (30-45) years of age. The incomes are then percentile ranked within cohorts at the national level for both fathers and sons.

Just as estimating intergenerational mobility amounts to choosing a statistic to characterize the joint distribution of parent and child income, measuring inequality amounts to choosing a metric to characterize the dispersion in a distribution. The most commonly used metric of inequality is the Gini coefficient, which readily incorporates changes in the dispersion across the whole distribution, and is therefore the preferred one in this study. There are numerous mathematically equivalent ways of defining the Gini coefficient (Yitzhaki, 1998). In this study, I define it as (half of) the relative mean absolute difference because of its intuitive interpretation as a function of the expected absolute income difference between two random draws from the income distribution. To see this, let y denote annual income, $\bar{y}$ the population average, and n the population size indexed by i and j. Then the Gini coefficient is given by:

$$G = \frac{\sum_{i=1}^{n} \sum_{j=1}^{n} |y_i - y_j|}{2n \sum_{i=1}^{n} y_i}$$

The Gini coefficient thus ranges between 0 and 1 where 0 means that everyone has the same income and 1 means that one individual has all the income. To measure childhood inequality, z_{rt}, I average the annual Gini coefficients (based on the labor market incomes defined in section 4.1 among male residents aged

18 to 64) in the commuting zone, from the year before birth until 18 years of age. Consequently, childhood inequality is given by:

$$z_{rt} = \frac{1}{20} \sum_{k=t_{-1}}^{t_{18}} G_{rk}$$

Here z_{rt} is the average inequality that cohort *t* raised in commuting zone *r* was exposed to from the year prior to birth (in utero) until 18 years of age.

I use data on educational attainment as well as cognitive and non-cognitive skills for the child generation in the decomposition exercise described in Section 2.1. The education data is reported in levels but have been converted into years of education as follows; old primary school = 7 years; new primary school = 9 years; short high school = 11 years; long high school = 12 years; short tertiary education = 14 years; long tertiary education = 16 years; and Ph.D. = 20 years.

The data on cognitive and non-cognitive skills come from military enlistment tests and are available from 1969 onwards in stanine scale measurements.[12] These tests were mandatory for all Swedish men and the enlistment typically took place the year a person turned 18 or 19 years old. Cognitive ability scores were based on tests on verbal, logical, spatial and technical abilities. In contrast, non-cognitive ability scores were based on semi-structured interviews with a certified psychologist with the explicit aim of assessing the enlistee's ability to cope with the psychological requirements of military service. According to the Swedish National Service Administration as reported by Lindqvist and Vestman (2011), the character traits that gave a high score during the enlistment interview were independence, persistence, willingness to assume responsibility, outgoing character, emotional stability, power of initiative, and social skills.

Table 1 reports descriptive statistics divided into 5-year cohort groups at the individual level. Average annual income for fathers increases slightly across cohorts; from 280 924 SEK for cohorts born 1961-1965 to 288 798 SEK for cohorts born 1976-1980. Likewise, the average number of observed incomes for fathers increases from 9 to 15, while the average age at which their income is observed declines slightly from 42 to 41. Sons' average annual income also

[12] Stanine is a method of scaling scores on a nine-point scale with mean equal to 5 and standard deviation equal to 2. To obtain stanines a normal distribution is divided into nine intervals with widths of 0.5 standard deviations, except for the first and last intervals which just contain the remainder of the scores.

increases slightly over the period, from 333,867 in the first cohort group to 364,253 in the last cohort group.

Table 1 Descriptive statistics at the individual level

	(1) 1961-1965	(2) 1966-1970	(3) 1971-1975	(4) 1976-1980	(5) All cohorts
Fathers					
Income	280 924	279 914	284 540	288 798	283 238
	(135 498)	(120 975)	(120 250)	(116 137)	(123 729)
Observed incomes	9.3	11.6	13.8	15.4	12.4
	(3.3)	(3.4)	(3.4)	(3.7)	(4.1)
Age	42.2	41.3	41.1	40.9	41.4
	(2.6)	(2.0)	(1.6)	(1.5)	(2.0)
Sons					
Income	333 867	364 729	369 483	364 253	358 025
	(176 854)	(182 089)	(163 456)	(137 255)	(167 944)
Observed incomes	14.1	13.3	9.2	4.9	10.7
	(3.2)	(2.9)	(2.1)	(1.4)	(4.4)
Age	37.5	36.9	34.6	32.1	35.5
	(1.3)	(1.3)	(1.0)	(0.8)	(2.4)
Years of education	12.0	12.3	12.8	13.2	12.6
	(2.5)	(2.5)	(2.5)	(2.3)	(2.5)
Cognitive ability	5.2	5.3	5.1	5.1	5.2
	(1.6)	(1.9)	(1.9)	(1.9)	(1.8)
Non-cognitive ability	5.2	5.2	5.2	5.1	5.2
	(1.6)	(1.6)	(1.7)	(1.7)	(1.6)
Cohort size	44 606	47 772	45 687	36 383	44 044
	(4 186)	(2 242)	(1 753)	(2 425)	(4 971)

Note. Columns 1-4 reports statistics within 5-year cohort spans and column 5 reports statistics across all cohorts. Cohort size refers to the sample sizes when mobility is estimated in each CZ for each cohort. Standard deviations are reported in parentheses.

The average number of observed incomes for sons decreases quite significantly, from 14 for the first cohort group to 5 for the last cohort group. Simultaneously, the average age at which their income is observed decreases from 38 to 32. These decreases in the number of observed incomes and the age at which incomes are observed is because incomes are only observed until 2012, which means that incomes are only observed between 30-32 years of age for the youngest cohort. The average years of education increases by one year, from 12 to 13, while cognitive and non-cognitive skills remain practically constant.

Table 2 reports population weighted descriptive statistics at the CZ level divided into 5-year groups that correspond to the cohort groups in the previous table.

Table 2 Descriptive statistics at the CZ level

	(1) 1961-1965	(2) 1966-1970	(3) 1971-1975	(4) 1976-1980	(5) All cohorts
IRP	0.276	0.283	0.259	0.216	0.261
	(0.060)	(0.056)	(0.056)	(0.068)	(0.065)
Gini coefficient	0.242	0.230	0.220	0.218	0.228
	(0.019)	(0.017)	(0.015)	(0.016)	(0.019)
Sample size	2 538	2 614	2 507	1 967	2 432
	(3 167)	(3 209)	(3 089)	(2 447)	(3 030)

Note. IRP refers to the intergenerational rank persistence obtained as the OLS estimate of the slope coefficient from a bivariate regression of son's income rank on paternal income rank. The income ranks are based on approximated lifetime incomes that have been ranked by cohort in the population. All variables are weighted with the CZ by cohort sample size from the IRP estimations. Standard deviations are reported in parentheses.

Average rank persistence drops substantially from 0.276 to 0.216, while the average inequality falls from 0.242 to 0.218. The average sample size is stable across the first three cohort groups and then drops from about 2 500 to 1967 in the last cohort group. Notice however that the standard deviation of the sample across commuting zones is very large, reflecting the vast differences in population size in the commuting zones. I will return to that issue later.

5 Results

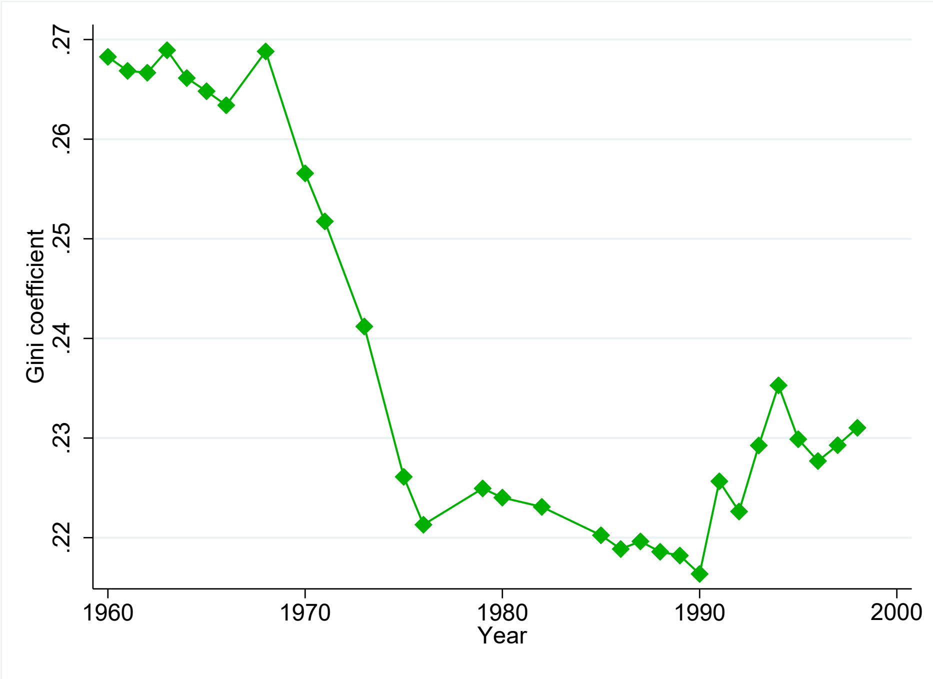
In this section, I first present results on the national inequality and mobility trends during the period. I then show what the regional variation in inequality and mobility looks like, before moving on to estimates of the Great Gatsby Curve. I also present new evidence on features of the Great Gatsby Curve.

5.1 National mobility and inequality trends

Figure 1 plots the national inequality level between 1960 and 1998 – corresponding to the years included in the childhood inequality measures.[13]

[13] The Gini coefficients are based on pre-tax labor market incomes (as defined in sections 4.1 and 4.2) among the male population aged 18-64.

Figure 1 National inequality



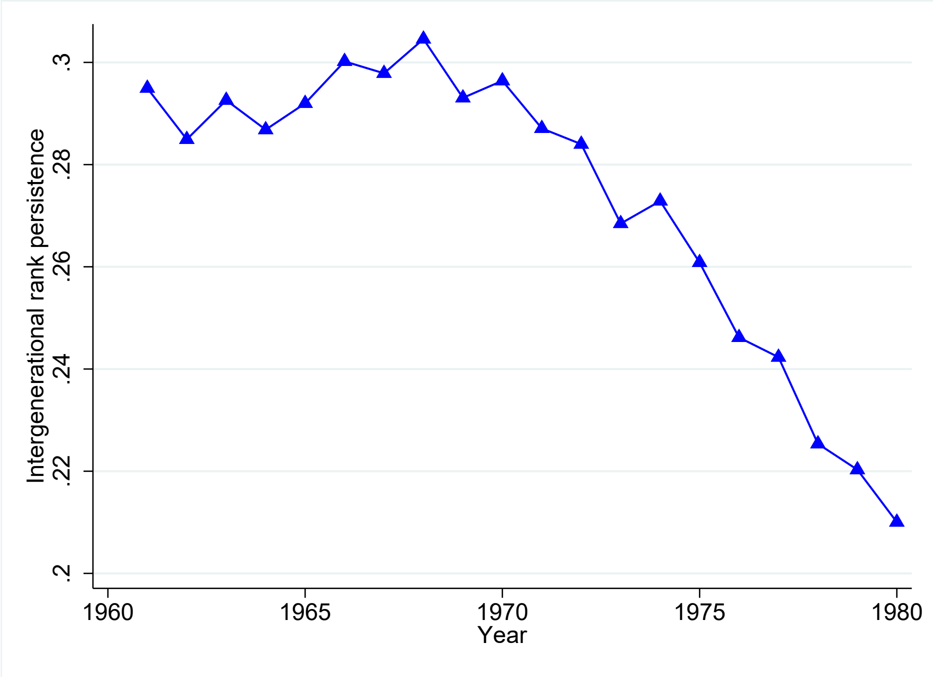
Notes. Inequality is measured as Gini coefficients based on pre-tax labor market incomes (defined in sections 4.1 and 4.2) among the male population aged 18-64.

Inequality was quite high for most of the 1960's at about 0.27 as measured by the Gini coefficient, but then fell to around 0.22 in 1975. Inequality then remained low until the beginning of the 1990's when it started to climb back up. These patterns are in line with previous studies on inequality in Sweden (Edin and Holmlund, 1993; Johansson et al., 2006; Domeij and Floden, 2010; Björklund and Jäntti, 2011).[14] The sharp wage compression at the end of the 1960's until the mid-1970's was to a large extent caused by decreasing age and education differentials in the labor market and falling returns to education (Edin and Holmlund, 1993). The increase in inequality during the 1990's however, was largely associated with increasing within-group dispersion given age, family composition and educational attainment (Domeij and Floden, 2010), and increasing wage dispersion between firms (Skans et al., 2009).

[14] The dissimilarities that do exist are likely caused by differences in sample restrictions and income definitions. For example, Björklund and Jäntti (2011) include capital income in their income measure and find that inequality increased during the 1980's, whereas I don't have information on capital income and find that inequality did not increase until 1990.

Figure 2 shows the intergenerational rank persistence at the national level for cohorts born between 1961 and 1980.

Figure 2 National rank persistence

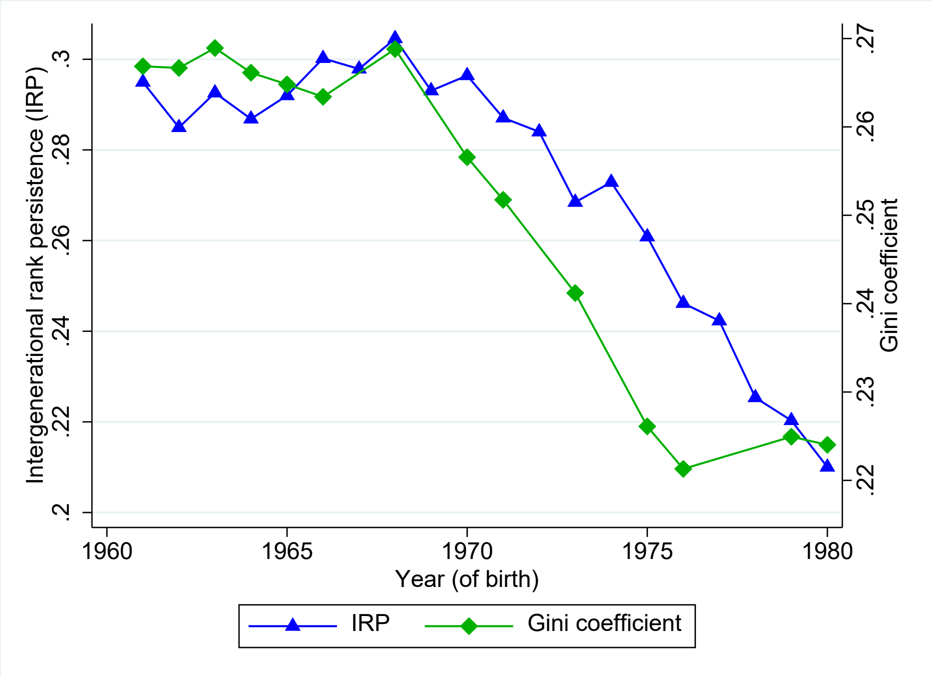


Notes. Intergenerational rank persistence is obtained as the slope coefficient from regressing sons' income rank on fathers' income rank. The income ranks are based on labor market incomes (as defined in sections 4.1 and 4.2) between 30-45 (30-50) years of age for sons (fathers). The percentile ranking is done by cohort in the population.

For cohorts born in the 1960's the IRP remains quite constant around 0.29. IRP then declines for the rest of the period to about 0.21 for the last cohort born in 1980, which means that later cohorts experienced higher levels of intergenerational mobility. These mobility patterns are in line with previous results in Björklund et al. (2009).[15] Hence, both inequality and intergenerational rank persistence falls over the period, and Figure 3 shows the striking co-movement between the two.

[15] The estimated IRP between 1960-1970 is somewhat sensitive to the age at which the incomes of sons are observed, but the decline after 1970 is not. When the observation window is limited to 30-35 years of age, the IRP declines about 0.03 points in 1960 and 0.01 points in 1970, and then converges with the trend plotted in Figure 2.

Figure 3 National rank persistence and inequality

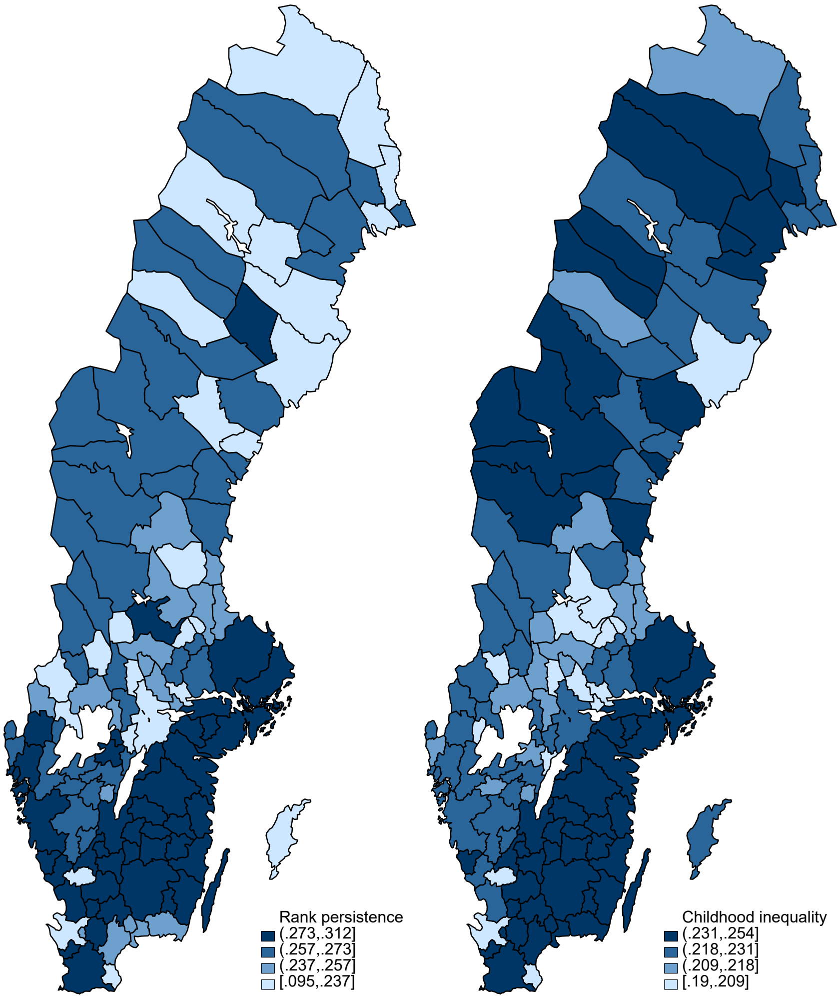


Notes. Intergenerational rank persistence is obtained as the slope coefficient from regressing sons' income rank on fathers' income rank. The income ranks are based on labor market incomes (as defined in sections 4.1 and 4.2) between 30-45 (30-50) years of age for sons (fathers). The percentile ranking is done by cohort in the population. Inequality is measured as Gini coefficients based on pre-tax labor market incomes (defined in sections 4.1 and 4.2) among the male population aged 18-64.

5.2 Regional mobility and childhood inequality

Choropleth maps of the regional distribution of intergenerational rank persistence and childhood inequality are shown in Figure 4. The maps are constructed by averaging the variables across cohorts within the commuting zones, and then grouping them into quartiles and shading them so that lighter colors correspond to smaller values.

Figure 4 Rank persistence and childhood inequality across commuting zones



Notes. The maps are created by averaging intergenerational rank persistence and childhood inequality across cohorts within commuting zones. The class breaks are defined by the quartiles of the distribution of each variable after averaging over cohorts.

With a couple of exceptions, areas with the highest intergenerational rank persistence are located in southern Sweden, including the commuting zones that contain the three largest cities in Sweden: Stockholm, Göteborg and Malmö. The regional differences in mobility are quite substantial, with Munkfors CZ exhibiting the highest level of rank persistence at 0.312, only 0.05 less than what Chetty et al. (2014) found for the United States.

The areas with high levels of childhood inequality are concentrated along the southeastern coastline and in some of the very large commuting zones in the north. Stockholm CZ exhibits the highest level of childhood inequality at 0.254, about three standard deviations higher than the (unweighted) average regional childhood inequality. In contrast, Olofström CZ exhibits the lowest inequality at 0.19, which is about 1.5 standard deviations lower than the average. To put these numbers into perspective, the difference between the most equal and unequal commuting zones in Sweden is about the same as the difference in inequality between Denmark and Canada (OECD, 2017).

5.3 The Great Gatsby Curve in Sweden

Table 3 reports results from estimating the Great Gatsby Curve in Sweden. Column 1 presents an unweighted OLS estimate of the slope coefficient in a regression of intergenerational rank persistence on childhood inequality at the CZ by cohort level, whereas columns 2-4 reports estimates weighted by the CZ by cohort sample sizes from the IRP estimations.

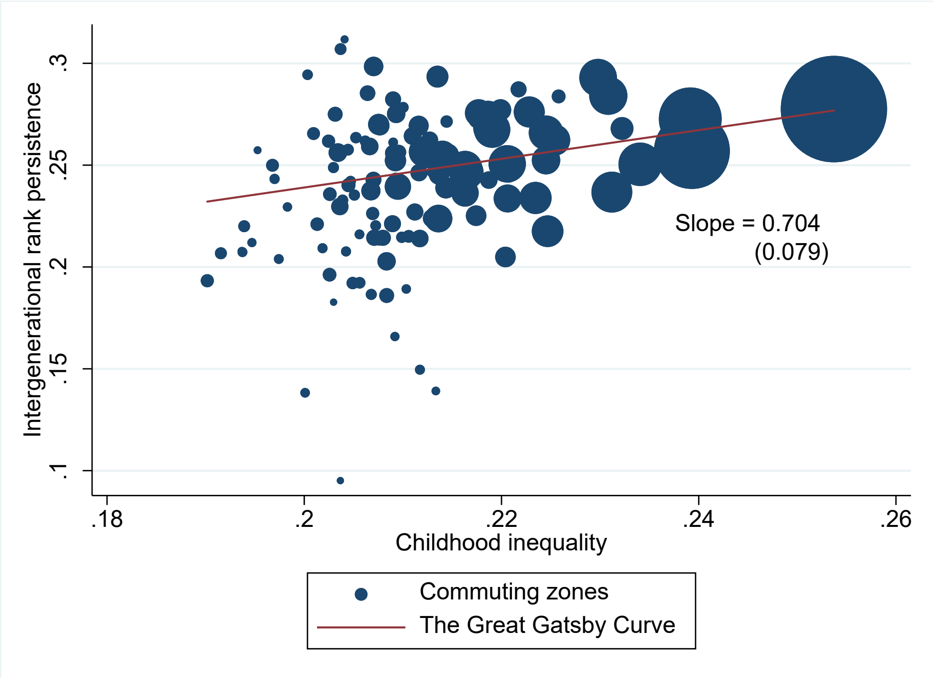
Table 3 The Great Gatsby Curve

	(1)	(2)	(3)	(4)
	Unweighted	Weighted	Cohort FE	CZ FE
Childhood inequality	1.466***	0.958***	0.693***	1.591***
	(0.172)	(0.0899)	(0.0805)	(0.359)
R^2	0.029	0.082	0.193	0.184
Observations	2 500	2 500	2 500	2 500

Notes. The outcome variable is intergenerational rank persistence (IRP). Column 1 reports an unweighted estimate and columns 2-4 reports estimates weighted by the CZ by cohort sample sizes from the IRP estimations. Standard errors are clustered at the commuting zone level in columns 1-3 and at the cohort level in column 4, and reported in parentheses.

Weighting reduces the estimated slope from 1.466 to 0.958, indicating that the relationship between inequality and mobility is weaker in commuting zones with relatively large populations or with characteristics that are positively correlated with having a large population (Solon et al., 2015). Weighting also dramatically increases precision – the standard error of the slope coefficient drops from 0.172 to 0.089, which means that some of the sparsely populated commuting zones have a large impact on the precision of the estimates. Figure 5 illustrates the issue: it plots the Great Gatsby Curve obtained by averaging inequality and mobility across cohorts within commuting zones.

Figure 5 The Great Gatsby Curve across commuting zones in Sweden



The size (and weight) of each data point is proportional to the average sample size in the commuting zone. The Great Gatsby Curve is clearly sloping upwards, which means that higher levels of childhood inequality is associated with less socioeconomic mobility. However, the plot also reveals a group of outliers in the lower left corner. These outliers are characterized by their low levels of intergenerational rank persistence given their levels of childhood inequality and their small populations, which explains the flatter slope and increased precision of the weighted estimates.

Turning back to Table 3, I find that a one-unit increase in childhood inequality is associated with a 0.958 increase in intergenerational rank persistence, which translates into a standard deviation increase in childhood inequality being associated with a 0.019 increase in intergenerational rank persistence. Taking these estimates at face value, average childhood inequality would have to increase by three standard deviations for the persistence of income across generations in Sweden to reach the same level as in the United States (Chetty et al., 2014).[16]

The third column of Table 3 reports the expected change in intergenerational rank persistence when cohort fixed effects are added. In this estimation, the identifying variation comes from comparing sons born in the same year but in different commuting zones. Revealingly, adding cohort fixed effects decreases the estimated slope from 0.958 to 0.693, implying that the association between inequality and mobility is positively related to national trends. Since the cohorts in the sample are born in 1961–1980, a strong candidate for such a trend is access to tertiary education, which vastly increased in the 1990's and 2000's (SOU, 2007:81). Other changes at the national level that the cohort fixed effects control for include the polarized job growth in recent decades (Adermon and Gustavsson, 2015), as well as the diminished role of centralized wage bargaining after 1983 and the sharp increase in labor market tightness during the 1990's (Holmlund, 2003).

Column 4 of Table 3 reports the estimated slope of the Great Gatsby Curve when fixed effects are added at the commuting zone level. This means that the variation used to estimate the association between inequality and mobility comes from sons born in different years within the same commuting zones. Consequently, the CZ fixed effects control for families selecting into CZ level residency. In contrast to cohort fixed effects, adding CZ fixed effects increases the estimated slope, suggesting that selection into residency reduces the association between childhood inequality and intergenerational rank persistence.

The take away from Table 3 is that the association between inequality and mobility holds even after controlling for constant differences across cohorts and commuting zones. The fact that sons who experience high levels of inequality during childhood on average experience less intergenerational mobility, regardless of whether they are compared to sons who grew up in the same commuting zone but were born in different years, or to sons born in the same year but in different commuting zones, suggest that the Great Gatsby Curve reflects a non-trivial relationship between inequality and socioeconomic mobility.

[16] Chetty et al. (2014) estimate that the U.S. rank persistence is 0.317 for cohorts born 1980-1982. See the second column of Table 1 where the individual income rank estimate for a sample restricted to male children is presented.

5.4 Inequality at different stages of childhood

I now turn to the question whether the association between inequality and rank persistence across generations is particularly strong during specific stages of childhood. To investigate this, I replace the childhood inequality measure with the average Gini coefficient during four developmental stages of childhood; the "baby years" (age -1 to 2), the "preschool years" (age 3 to 6), the "school years" (age 7 to 12) and the "teen years" (age 13 to 18). Panel A of Table 4 reports estimates from bivariate regressions of intergenerational rank persistence on the average inequality at each stage of childhood.

Table 4 Inequality at different ages

	(1) Baby years	(2) Preschool years	(3) School years	(4) Teen years
	-1 to 2	3 to 6	7 to 12	13 to 18
Panel A				
Childhood inequality	0.926***	0.842***	0.910***	0.561***
	(0.0629)	(0.0621)	(0.0743)	(0.0884)
R^2	0.13	0.09	0.07	0.02
Panel B				
Childhood inequality	1.378***	-0.199	0.184	-0.920***
	(0.122)	(0.191)	(0.174)	(0.204)
R^2	0.15	0.15	0.15	0.15
Observations	2 500	2 500	2 500	2 500

Notes. Panel A reports OLS estimates from bivariate regressions of intergenerational rank persistence on the average (CZ by cohort) inequality during the age span, along with the R^2. Panel B reports estimates of the partial effect of inequality within each age span given inequality at all other age spans. All estimates are obtained using sample size weights from the IRP estimations. Standard errors are clustered at the commuting zone level and reported in parentheses.

As we can see, the point estimates during the baby years, the pre-school years, and the school years are quite similar in size at around 0.9, while inequality during the teen years is much lower at 0.56. Furthermore, inequality during the baby years explains the most variance with an R^2 of 0.13, compared with only 0.02 during teen years, indicating that the association between inequality and intergenerational mobility is strongest during the earliest stages of life.

Panel B reports the partial effects of inequality at each age span. Here we can see that inequality during the baby years has the strongest conditional effect on intergenerational mobility with a point estimate of 1.38, compared to statistically insignificant estimates during the pre-school and school years. However, the partial effect of inequality during the teen years has a negative effect on intergenerational rank persistence with a point estimate of -0.92. This suggests that the relationship between inequality and mobility changes over the different stages of childhood. However, caution is warranted when interpreting these results given the autocorrelated nature of regional inequality levels.

5.5 Level effects of childhood inequality

To investigate whether the Great Gatsby Curve is constant across the inequality distribution, I fit a linear spline to the data by partitioning it into three parts using two equidistant points between the lowest and highest observed childhood inequality. The bottom segment ranges from 0.18-0.21, the middle segment from 0.21-0.25, and the upper segment from 0.25-0.28. The spline coefficients measures the expected change in intergenerational income persistence following a one-unit change in inequality given that the change occurs at the specific segment of the inequality distribution. The estimates are reported in Table 5.

Table 5 Inequality at different ages

	(1) Global	(2) 0.18–0.21	(3) 0.21–0.25	(4) 0.25–0.28
Childhood inequality	0.958***	1.955***	0.629	1.161***
	(0.090)	(0.413)	(0.203)	(0.168)
$P(\theta_k = \theta_{global})$		0.017**	0.109	0.227
$P(\theta_k = \theta_{k-1})$			0.020**	0.082*
Observations	2 500	1616	843	41
R^2	0.082	0.086	0.086	0.086

Notes. Column 1 shows the estimated Great Gatsby Curve across commuting zones and cohorts in Sweden. Columns 2-4 reports the slope coefficient from regressing intergenerational rank persistence on childhood inequality in the respective segments of the inequality distribution. The third row shows the probability that the slope estimate in the segment is equal to the global slope, and the fourth row show the probability that the slope estimate in the segment is equal to the slope estimate in the preceding segment. All estimates are obtained using sample size weights from the IRP estimations. Standard errors are clustered at the CZ level and reported in parentheses.

The first row reports the estimated slope coefficients in each segment, the second row reports the probability that those slopes are equal to the global slope of 0.958, and the third row reports the probability that the slope in the segment is equal to the slope in the preceding segment. The only slope that is significantly different from the global slope is the slope in the first segment, suggesting that inequality that increases from a low level has a relatively large impact on intergenerational mobility.

6 Mechanisms

In this section, I first present the results from decomposing the transmission of income across generations. I then describe how the mediation effects are related to childhood inequality, and how those relationships differ when inequality increases due to changes above or below the median of the income distribution.

6.1 The mediators of intergenerational mobility

The top row of Table 6 shows the decomposition of intergenerational rank persistence into four orthogonal channels: educational attainment; cognitive skills; non-cognitive skills; and a residual effect that captures the conditional effect of paternal income rank on the income rank of the son after controlling for the other channels.

Table 6 Mediators of intergenerational mobility

	(1)	(2)	(3)	(4)	(5)
	Total persistence	Education	Cognitive ability	Non-cognitive ability	Residual effect
Panel A					
IRP	0.26	0.05	0.04	0.04	0.12
	(100%)	(21%)	(16%)	(16%)	(45%)
Panel B					
IRP		0.095	0.062	0.047	
		(36%)	(24%)	(18%)	
Observations	2 500	2 500	2 500	2 500	2 500

Notes. In panel A, column 1 reports the average intergenerational rank persistence across 20 cohorts and 125 commuting zones. Sons are born 1961-1980 and their income is observed at approximately 35 years of age. Fathers are born 1920-1960 and income is observed at approximately 41 years of age. The sample is restricted to sons who lived in the same CZ at least 6 years between 2 and 12 years of age. Columns 2-4 report the average mediation effect of education, cognitive skill and non-cognitive skill across CZ's in the persistence of income across generations. Column (5) reports the persistence of income across generations that remain after the other variables are accounted for. In panel B, column (2) reports the mediation effect of education when cognitive and non-cognitive skills are excluded from the decomposition, while columns 3-4 reports the mediation effects of cognitive and non-cognitive skills when education is excluded from the decomposition.

The three mediating variables collectively account for about 53 percent of the total persistence of income ranks across generations, leaving about 45 percent accounted for by the residual effect.[17] Among the mediating variables,

[17] The percentages do not sum to 100 due to round off errors.

educational attainment accounts for the largest part at 21 percent, while cognitive and non-cognitive skills account for about 16 percent each.

Children with good social skills, high perseverance and a high capacity for abstract and logical thinking naturally do well in school and therefore select into higher education. This begs the question to what extent cognitive and non-cognitive skills beget educational attainment, and conversely what the role of schooling is in the formation of cognitive and non-cognitive skills?[18] To investigate this, I first estimate the returns to education conditional only on paternal income rank:

$$y_{irt} = \gamma_{rt} + \pi_{1rt} e_{irt} + \delta_{2rt} y_i^p + \upsilon_{irt}$$

Recall that ρ_{1rt} is an estimate of the returns to education conditional on paternal income rank as well as cognitive and non-cognitive skills. Therefore, the difference between $\pi_{1rt}\varphi_{1rt}$ and $\rho_{1rt}\varphi_{1rt}$ captures the extent that the son's cognitive and non-cognitive skills generate intergenerational rank persistence by enabling higher educational attainment.

Next, I estimate the returns to cognitive and non-cognitive skills conditional only on parental income:

$$y_{irt} = \gamma_{rt} + \pi_{2rt} c_{irt} + \pi_{3rt} n_{irt} + \delta_{3rt} y_i^p + \upsilon_{irt}$$

The difference between $\pi_{2rt}\varphi_{2rt}$ and $\rho_{2rt}\varphi_{2rt}$, and $\pi_{3rt}\varphi_{3rt}$ and $\rho_{3rt}\varphi_{3rt}$, is the difference between the mediating effect of skills when the mediating effect education is and is not accounted for. It therefore captures the extent that schooling contributes to intergenerational rank persistence by affecting the development of cognitive and non-cognitive skills, and the labor market returns to those skills.

The estimates of $\pi_{1rt}\varphi_{1rt}$, $\pi_{2rt}\varphi_{2rt}$ and $\pi_{3rt}\varphi_{3rt}$ are shown in panel B of Table 6. When skills are excluded from the returns estimation, the mediating effect of schooling increases from 21 percent of the intergenerational rank persistence to 36 percent. Taking these estimates at face value, they imply that selection into education due to cognitive and non-cognitive skills account for as much as 42 percent of the mediating effect of educational attainment. Turning to the role of schooling for the contribution of cognitive and non-cognitive skills to intergenerational rank persistence, I find that the mediating effect of cognitive

[18] In the child generation, the correlation is 0.53 between education and cognitive skills, and 0.31 between education and non-cognitive skills. The correlation between cognitive and non-cognitive skills is 0.37.

skills increases from 16 to 24 percent when education is not accounted for, and that the mediation effect of non-cognitive skills increases from 16 to 18 percent. This implies that schooling account for about a third of the mediating effect that cognitive skills have on intergenerational income persistence, but only about 11 percent of the contribution that non-cognitive skills have.

6.2 The mechanisms of the Great Gatsby Curve

Panel A of Table 7 reports OLS estimates of the association between the mediation effects ($\pi_{1rt}\varphi_{1rt}$, $\pi_{2rt}\varphi_{2rt}$, $\pi_{3rt}\varphi_{3rt}$, and δ_{1rt}) and childhood inequality.

Table 7 The mechanisms of the Great Gatsby Curve

	(1)	(2)	(3)	(4)	(5)
	Total persistence	Education	Cognitive skills	Non-cognitive skills	Residual effect
Panel A					
Childhood	0.958***	0.318***	0.299***	0.291***	0.0459
inequality	(0.0899)	(0.0780)	(0.0437)	(0.0212)	(0.0697)
	[0.287]	[0.219]	[0.257]	[0.276]	[0.0149]
R^2	0.082	0.048	0.066	0.076	0.000
Panel B					
Childhood inequality	-	0.640***	-	-	0.318***
		(0.117)			(0.0669)
Childhood	-	-	0.452***	0.319***	0.187***
inequality			(0.0746)	(0.0227)	(0.0536)
Observations	2 500	2 500	2 500	2 500	2 500

Notes. In panel A, column 1 reports the estimated slope coefficient from a regression of intergenerational rank persistence on childhood inequality. Columns 2-5 report the corresponding estimates from separately regressing the mediation effects and the residual effect on childhood inequality. In panel B, estimates are reported when skills/educational attainment are excluded from the decomposition analysis. Standardized estimates are reported in square brackets, and all estimates are obtained using sample size weights from the IRP estimations. Standard errors are clustered at the CZ level and reported in parentheses.

The most striking result is that the residual effect is uncorrelated with inequality. This is indeed a surprising result since the residual effect account for nearly half of the total persistence of income ranks across generations. It implies that the Great Gatsby Curve is entirely driven by the mediating effects that the son's educational attainment and development of cognitive and non-cognitive skills have on the intergenerational rank persistence.

Standardized coefficients are reported in square brackets, and a one standard deviation increase in childhood inequality is associated with a 0.22 standard deviation increase in the mediating effect of educational attainment on the intergenerational rank persistence. The corresponding estimates for the son's cognitive and non-cognitive skills are 0.26 and 0.28 respectively, which suggest that the three channels of income transmission are just about equally responsive to changes in inequality during childhood.

Panel B of Table 7 shows how the mediating effect of educational attainment is related to childhood inequality when cognitive and non-cognitive skills are excluded from the decomposition analysis, and vice versa. However, as we saw in section 6.1, educational attainment does not pick up all of the rank persistence accounted for by cognitive and non-cognitive skills. Hence, the expected change in the residual effect following a one-unit increase in childhood inequality increases from 0.05 to 0.32, while the expected change in the mediating effect of educational attainment increases from 0.32 to 0.64. This means that the mediating effect of educational attainment absorbs about half of the association between childhood inequality and the mediating effects of cognitive and non-cognitive skills, while the rest is soaked up by the residual effect.

When educational attainment is excluded from the decomposition analysis, the expected change in the mediating effect of the son's cognitive and non-cognitive skills following a one-unit increase in childhood inequality increases from 0.30 to 0.45 and from 0.29 to 0.32 respectively. The remaining rank persistence that the son's educational attainment accounts for is absorbed by the residual effect, whose expected change following a one-unit increase in childhood inequality increases to 0.19.

In conclusion, the Great Gatsby Curve is driven by the mediating effect that children's educational attainment and development of cognitive and non-cognitive skills have on the persistence of socioeconomic status across generations. Failing to account for educational attainment or cognitive and non-cognitive skills causes an upward bias of the remaining mediating effects, as well as a large increase in the residual effect that can easily be misinterpreted as a significant association between childhood inequality and a direct effect of parental income on children's income.

6.3 Disentangling attainment from returns

Now that we have seen that the mediating effects of educational attainment and cognitive and non-cognitive skills are all positively associated with childhood inequality, it is natural to ask whether this reflects a relationship between the attainment/development of these mediators, or with their labor market returns?

To disentangle attainment/development from returns, panel A of Table 8 reports the results of regressing φ_{1rt}, φ_{2rt}, and φ_{3rt} on childhood inequality. Hence, it reports OLS estimates of the relationship between childhood inequality and the association between paternal income rank and the son's attainment of the mediating variables. [19]

Table 8 Childhood inequality and attainment/returns to mediating variables

	(1)	(2)	(3)
	Education	Cognitive skills	Non-cognitive skills
Panel A			
Childhood inequality	0.141***	0.0590***	0.0341***
	(0.0780)	(0.0437)	(0.0212)
	[0.449]	[0.247]	[0.167]
Panel B			
Childhood inequality	0.218	10.293***	14.528***
	(1.407)	(2.018)	(1.675)
	[0.004]	[0.175]	[0.243]
Observations	2 500	2 500	2 500

Notes. Panel A reports OLS estimates of the slope coefficients from regressing φ_{1rt}, φ_{2rt}, and φ_{3rt} on childhood inequality, shown in columns 1, 2, and 3 respectively. Hence, it reports the estimated relationship between childhood inequality and the association between paternal income rank and the son's attainment of the mediating variables. Panel B reports OLS estimates of the slope coefficients from regressing ρ_{1rt}, ρ_{2rt}, and ρ_{3rt} on childhood inequality. Hence, it reports the estimated relationship between childhood inequality and the conditional returns to the mediating variables. Standardized estimates are reported in square brackets, and all estimates are obtained using sample size weights from the IRP estimations. Standard errors are clustered at the CZ level and reported in parentheses.

The association between paternal income rank and the son's attainment of all three mediating variables are positively correlated with inequality during childhood. Standardized estimates are reported in square brackets, and a one standard deviation increase in childhood inequality is associated with a 0.45 standard deviation increase in the mediating effect of the son's educational attainment on intergenerational rank persistence. The corresponding estimates for the mediating effects of the son's cognitive and non-cognitive skills are 0.25 and 0.17 respectively.

[19] Recall that φ_{1rt}, φ_{2rt}, and φ_{3rt} are the slope coefficients obtained from regressing the educational attainment and development of cognitive and non-cognitive skills of sons on paternal income ranks.

Panel B reports the results of regressing ρ_{1rt}, ρ_{2rt}, and ρ_{3rt} on childhood inequality; i.e. it reports OLS estimates of the relationship between the conditional returns to the mediating variables and childhood inequality. As we can see, inequality during childhood is positively correlated with the son's conditional returns to cognitive and non-cognitive skills, but uncorrelated with the conditional returns to educational attainment. A one standard deviation increase in childhood inequality is associated with a 0.18 standard deviation increase in the conditional returns to cognitive skills, and a 0.24 standard deviation increase in the conditional returns to non-cognitive skills.

In conclusion, paternal income rank has a stronger association with the son's educational attainment and development of cognitive and non-cognitive skills in regions and/or periods with high levels of inequality. In addition, inequality during childhood is positively correlated with the conditional returns to skills, but not with the conditional returns to education.

6.4 The mediators of mobility and inequality above or below the median

To investigate whether inequality during childhood ha a different effect on the mediators of intergenerational rank persistence at different parts of the inequality distribution, Table 9 presents the results from regressing intergenerational rank persistence and the mediating effects on childhood inequality as measured by the 90-50 and 50-10 percentile ratios of the income distribution respectively.

A one-unit increase of the 90-50 percentile ratio during childhood is associated with a 0.17 increase in intergenerational rank persistence, while a one-unit increase in the ratio of the 50-10 percentile ratio is associated with a 0.31 increase, indicating that rank persistence is more responsive to changes in childhood inequality at the bottom half of the income distribution.

Focusing on the mediators on intergenerational rank persistence, I find that the mediating effects skills are positively correlated with inequality above as well as below the median. However, the mediating effect of education is positively correlated with inequality above the median but uncorrelated with inequality below the median. This implies that paternal income rank is expected to have a stronger association with the son's educational attainment when the difference between the relatively wealthy and the median earner is large, but not when the difference between the relatively poor and the median earner is large. A conceivable interpretation of this is that the scope for parents to invest in their children's educational attainment in Sweden is limited to the top of the parental income distribution.

Table 9 Mediators of mobility and inequality above and below the median

	(1)	(2)	(3)	(4)	(5)
	Total persistence	Education	Cognitive skills	Non-cognitive skills	Residual effect
P_{90}/P_{50}	0.171***	0.0509***	0.0515***	0.0598***	0.0083
	(0.0189)	(0.0197)	(0.0091)	(0.0042)	(0.0173)
R^2	0.060	0.028	0.045	0.074	0.000
P_{50}/P_{10}	0.309***	0.0405	0.116***	0.100***	0.0510**
	(0.0766)	(0.0409)	(0.0217)	(0.0196)	(0.0254)
R^2	0.043	0.004	0.049	0.045	0.001
Observations	2 500	2 500	2 500	2 500	2 500

Notes. Column 1 reports the OLS estimate of the slope coefficient from regressing intergenerational rank persistence on childhood inequality as measured by the 90-50 and 50-10 percentile ratios of the income distribution respectively. Columns 2-5 report the corresponding estimates for the mediators of intergenerational rank persistence. All estimates are obtained using sample size weights from the IRP estimations. Standard errors are clustered at the CZ level and reported in parentheses.

In contrast, the residual effect is uncorrelated with inequality above the median, but positively correlated with inequality below the median. Hence, the channels of intergenerational rank persistence picked up by the residual effect (such as social networks, hereditary traits, and direct effects of paternal income rank) are expected to have a stronger impact on the son's socioeconomic status in rearing environments where the difference between the relatively poor and the median earner is large, but not where the difference between the relatively rich and the median earner is large.

7 Robustness analysis

In this section I investigate whether the results in section 5 are robust to the choice of inequality metric to characterize the dispersion in the income distributions, and to the choice of mobility statistic to characterize the joint distribution of parent and child income. I investigate whether they are robust to the level of the minimum income restriction described in section 4.1.

7.1 Alternative measures of inequality and mobility

Table 10 reports output from estimating the Great Gatsby Curve using both the intergenerational rank persistence and the intergenerational elasticity of income as mobility statistics, and the Gini coefficient, the mean log deviation (MLD), and the 90-10 percentile ratio as inequality metrics.

Table 10 Inequality metrics and mobility statistics

	(1) Unweighted	(2) Weighted	(3) Cohort FE	(4) CZ FE
IRP				
Gini coefficient	1.466***	0.958***	0.693***	1.591***
	(0.172)	(0.0899)	(0.0805)	(0.359)
Mean log deviation	2.118***	1.268***	0.930***	1.965***
	(0.249)	(0.130)	(0.102)	(0.450)
P_{90}/P_{10}	0.126***	0.0817***	0.0579***	0.187***
	(0.0195)	(0.0093)	(0.0064)	(0.0395)
IGE				
Gini coefficient	1.910***	1.275***	0.779***	2.450***
	(0.206)	(0.115)	(0.103)	(0.590)
Mean log deviation	2.770***	1.695***	1.049***	3.002***
	(0.295)	(0.174)	(0.124)	(0.744)
P_{90}/P_{10}	0.174***	0.108***	0.0672***	0.287***
	(0.0237)	(0.0121)	(0.0075)	(0.0647)
Observations	2 500	2 500	2 500	2 500

Notes. The outcome variable is intergenerational rank persistence (IRP) and intergenerational income elasticity (IGE) respectively. Column 1 reports unweighted estimates and columns 2-4 reports estimates weighted by the CZ by cohort sample sizes from the mobility estimations. Standard errors are clustered at the commuting zone level in columns 1-3 and at the cohort level in column 4, and reported in parentheses.

The MLD is relatively sensitive to changes near the bottom of the income distribution, and therefore complements the Gini coefficient (which is sensitive to changes in the middle of the distribution). Let y denote annual income, $\bar{y}$ the population average, and n the population size indexed by i. Then the MLD is defined as:

$$MLD = \frac{1}{n}\sum_{i=1}^{n} ln\left(\frac{\bar{y}}{y_i}\right)$$

The 90-10 percentile ratio is a common statistic in the literature with the benefit of being easy to interpret, but nevertheless incorporates less information about the dispersion of the income distribution since it abstracts from changes at all other percentiles.

I find that sons that were exposed to higher levels of inequality during childhood experienced less intergenerational mobility across all six combinations of mobility statistics and inequality metrics. Furthermore, adding weights and fixed effects has the same qualitative effect in all specifications in terms of the impact on precision and the direction of the change in the estimated slope coefficients. Hence, the results are not sensitive to the choice of the mobility statistic and inequality metric.

7.2 Minimum income levels

Table 11 also reports output from estimating the Great Gatsby Curve using mobility and inequality measures that are based on minimum income levels that are either half as large or twice as large as the preferred minimum income level (described in section 4.1).

Table 11 Minimum income levels

	(1) Unweighted	(2) Weighted	(3) Cohort FE	(4) CZ FE
Childhood inequality				
Preferred minimum	1.466***	0.958***	0.693***	1.591***
income	(0.172)	(0.0899)	(0.0805)	(0.359)
Half the minimum	1.001***	1.014***	0.592***	1.325***
income	(0.156)	(0.0818)	(0.154)	(0.249)
Twice the minimum	1.301***	1.017***	0.997***	0.993***
income	(0.165)	(0.0768)	(0.0948)	(0.300)
Observations	2 500	2 500	2 500	2 500

Notes. The outcome variable is intergenerational rank persistence (IRP) and the dependent variable is childhood inequality, both of which are based on either the preferred minimum income level as described in section 4.1, or on half its level or twice its level. Column 1 reports unweighted estimates and columns 2-4 reports estimates weighted by the CZ by cohort sample sizes from the mobility estimations. Standard errors are clustered at the commuting zone level in columns 1-3 and at the cohort level in column 4, and reported in parentheses.

The first row reports estimates based on the preferred minimum income as a reference point. The second row reports estimates based on minimum incomes that are half as large, and looking at column 1 and 2 we can see that the unweighted estimate is smaller (1.001 compared to 1.466 in the first row) but that the weighted estimate is larger (1.014 compared to 0.958). The effect of doubling the minimum income level is reported in the third row, and it follows the same pattern; the unweighted estimate is slightly smaller at 1.301 compared to 1.466 and the weighted estimate is slightly larger at 1.017 compared to 0.958. However, most of these differences are not statistically significant and therefore does not indicate that the results are sensitive to the level of the minimum income restriction.

8 Conclusion

I estimate the Great Gatsby Curve - a curve depicting the relationship between inequality during childhood and intergenerational mobility - across 125 commuting zones in Sweden for 20 male cohorts born between 1961 and 1980, and find that sons who were exposed to higher levels of inequality during childhood also experienced less intergenerational mobility. Hence, I find that the Great Gatsby Curve exists in Sweden - a country with a high degree of institutional homogeneity across regions, thereby addressing previously raised concerns about the validity of cross-country studies. I also find that high levels of inequality is associated with low levels of mobility even when adding commuting zone (cohort) fixed effects to the model, thereby relying exclusively on longitudinal (cross-sectional) variation in inequality to estimate the slope of the Great Gatsby Curve. In other words, men that were exposed to high levels of inequality during childhood experienced less intergenerational mobility compared to men born in the same year but in a different commuting zone, and compared to men born in the same commuting zone but in a different year.

I also study two features of the Great Gatsby Curve. First, I estimate the relationship between intergenerational mobility and inequality at different stages of childhood, and find that inequality during the earliest stage of childhood (age -1 to 2) has the strongest association with intergenerational mobility. Second, I fit a linear spline function to the childhood inequality distribution and estimate the relationship between intergenerational mobility and inequality at different levels, and find that childhood inequality has a stronger association with intergenerational mobility at the lower end of the inequality distribution.

I then decompose the intergenerational rank persistence into four separate channels to study the underlying mechanisms that drive the Great Gatsby Curve. These channels are the son's educational attainment, cognitive skills, non-cognitive skills, and a residual effect that captures the remaining persistence of income ranks across generations once the other mediating variables have been accounted for. I find that the son's educational attainment accounts for approximately 21 percent of the intergenerational rank persistence, while the son’s development of cognitive and non-cognitive skills account for about 16 percent each, leaving almost half of the rank persistence accounted for by the residual effect. However, when estimating the relationship between the transmission channels and childhood inequality I find that childhood inequality is uncorrelated with the residual effect. In contrast, all three mediating variables are positively correlated with childhood inequality, implying that what drives the Great Gatsby Curve is the association between inequality during childhood and the mediating effects that children's educational attainment and development of cognitive and non-cognitive skills have on the persistence of socioeconomic status across generations.

In conclusion, this paper makes two significant contributions to the literature on intergenerational mobility and the Great Gatsby Curve. First, I estimate the Great Gatsby Curve across institutionally and methodologically homogeneous units, thereby addressing earlier criticism of cross-country studies. Second, I decompose the transmission of socioeconomic status across generations into particular channels, and find that inequality during childhood is associated with the magnitude of these channels in different ways and to different extents. Hence, the descriptive evidence presented in this study of the Great Gatsby Curve strongly suggests that there is more to the relationship between inequality and mobility than happenstance outcomes originating in methodological choices and measurement errors.

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