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ABSTRACT

Most previous studies of intergenerational transmission of human capital are restricted to two generations: how parents influence their children. In this study, we use a Swedish data set that links individual measures of lifetime earnings for three generations and data on educational attainment for four generations. We find that estimates obtained from data on two generations severely underestimate long-run intergenerational persistence in both labor earnings and educational attainments. Long-run social mobility is hence much lower than previously thought. We attribute this additional persistence to "dynastic human capital"—the influence on human capital of more distant family members than parents.

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I. Introduction

Although concern for long-term social mobility is a fundamental motivation for the study of intergenerational transmission of human capital, most theoretical and empirical studies have been limited to the relation between two generations: parents and their children. The Becker-Tomes model—by far the most important model for intergenerational transmission of human capital—relates financial and other resources of the parent generation to the outcome of the child generation.[1] Empirical studies, as surveyed in Solon (1999) and Black and Devereux (2010), are with few exceptions restricted to two generations.[2]

Estimates from two-generation studies are often used to predict the persistence of long-run income inequality. A frequently cited example, Borjas (2009), is based on an initial income difference of 20 percent between two families. If there is an intergenerational correlation of 0.3, we expect only 30 percent of this difference—or six percentage points—to remain in the second generation. In the third generation, the difference is almost entirely eliminated, as only 1.8 percent is expected to remain. The canonical paper by Becker and Tomes (1986) concludes that in the United States and other rich countries, unless victimized by ethnic discrimination: "Almost all earnings advantages and disadvantages of ancestors are wiped out in three generations."[3] However, recent research has shown that the validity of this prediction relies heavily on which underlying transmission model is assumed (Clark 2012; Solon 2013; Stuhler 2013). In fact, such an underlying model cannot easily be recovered from data only covering two generations and predictions based on two generations can therefore be very misleading.

The main purpose of this paper is to investigate to what extent conventional estimates of intergenerational mobility based on data from two consecutive generations can predict long-term intergenerational mobility in human capital. For this purpose, we first simply predict long-term mobility measures for earnings and educational attainment from two-generation data and compare the predictions with actual mobility measures obtained when comparing cohorts two and three generations apart, respectively. We find that mobility is overestimated for both education and earnings.

We estimate two additional models. First, we use grandparent human capital outcomes as instruments for the corresponding outcomes in the parental generation to test the hypothesis of Clark (2012) that long-run social mobility is underestimated due to generation-specific deviations from the long-run social position of a family.[4] We reject the null hypothesis that the AR(1) model would give consistent estimates of long-run

1. Dynamic macroeconomic models of human and physical capital investments, fertility and inequality, as well as models of cultural transmission, focus on the link between two consecutive generations (Diamond 1965; Becker, Murphy, and Tamura 1990; Galore and Zeira 1993; Bisin and Verdier 2000; Mulligan 1997; and Saez-Marti and Sjögren 2008).

2. Examples of some studies that estimate the relationship between outcomes for grandparents and grandchildren are Behrman and Taubman (1985), Chan and Boliver (2013), Jaeger (2012), Lucas and Kerr (2012), Marchon (2008), Maurin (2002), Plug and Vijverberg (2005), Sacerdote (2005), Sauder (2006), and Warren and Hauser (1997).

3. It draws this strong and influential conclusion despite the fact that it recognizes the possibility of direct influences of grandparents already in the authors' 1979 paper and despite their awareness that persistence estimates failing to include grandparents are likely biased downward.

4. We thank Hoyt Bleakley and a referee for suggesting this test.

intergenerational mobility. However, this just-identified model does not allow us to test the validity of our instrumental variable. Second, we extend the Galtonian AR(1) model by also including grandparents' human capital outcomes in the regression. Our findings suggest that grandparents' outcomes have an independent effect on the outcomes of the grandchildren in these models.

Borjas (1992) attributed the slow convergence in human capital between different ethnic groups in the United States to "ethnic capital"—that is, the quality of the ethnic environment and the average skills of the parental generation of the ethnic group in which the child grows up. Analogous to his argument, our results suggest that we can attribute the stronger persistence in human capital outcomes to "dynastic human capital," or influences of more distant family members than parents.

We use an exceptional data set containing measures of lifetime earnings for three consecutive generations and educational attainment for four generations. The data set Generations Emanating from the Malmö Survey (GEMS) is based on a survey of all third graders in Sweden's third largest city, Malmö, and its suburbs, in 1938. This index generation subsequently has been followed until retirement and information about parents, spouses, children, and grandchildren has been added. The first generation—that is, the parents of the initially surveyed children—was, on average, born in the late 19th century, and their great-grandchildren, who constitute the fourth generation, typically completed or are in the process of completing their education in the early 21st century. Altogether, the data set includes 901 complete dynasties—that is, families where education data are available for at least one individual in each of four consecutive generations.

Compared to other Swedish register data and international data sets such as the Michigan Health and Retirement Study (HRS) and the Survey of Health Aging and Retirement in Europe (SHARE), the data set has two unique features that make it particularly useful for the present study. First, it has detailed income measures covering several years already in the 1930s, as well as information on educational attainments, for the first generation. Second, it has income measures for the second generation starting in the 1940s and covering the entire life cycle for the second generation. This enables us to obtain measures of educational attainments for four generations and detailed income measures for three generations.

The extensions of the empirical analysis of intergenerational mobility beyond two generations in this study relate to several additional strands in the literature on equality of opportunity and socioeconomic mobility across generations. As pointed out in Solon (1999) or Björklund et al. (2010), the "explained" variation in models based on siblings correlations is in general much higher than in models based on intergenerational correlations (around 0.3 compared to around 0.1). A plausible interpretation of this difference is that siblings share more characteristics than just parents. The potential influence of grandparents and great-grandparents—or dynastic capital—is obviously one of these shared characteristics that in addition to the influence of neighborhoods during adolescence, schools, and other environmental factors that siblings in most cases share, may affect their economic position as adults.

A recent literature, following Roemer (1993), aims at measuring the degree of equality of opportunity in a society; see, for example, Aaberge et al. (2010) or Björklund et al. (2012). Generations beyond the parental generation constitute an obvious "circumstance" that may influence the economic position of the child generation in addition to the investment decisions and endowments of the parent generation, as suggested in the Becker-Tomes model. There is also a literature, primarily in sociology, that has related child socioeconomic outcomes to those of members of the extended family, such as grandparents, aunts, uncles, and cousins (see, for example, Meier Jæger 2012; Monserud and Elger 2011; and Loury 2006). This literature also relates to the literature on group or ethnic effects in intergenerational mobility following Borjas (1992).

Our conclusion that the persistence in outcomes measured over several generations is much greater than what can be predicted from estimates based on correlations between parents and children can be generalized to other settings and outcomes. This is suggested in several recent studies using data from more than two consecutive generations. Long and Ferrie (2013), which analyzes occupational persistence in the United States and the United Kingdom, finds the same pattern, which is also true for Halphen Boserup et al. (2013), which analyzes wealth persistence in Denmark. These results are also supported by findings in Clark (2012) and Clark and Cummins (2012) for different measures of social status, using surnames to link generations during almost two centuries in Sweden and England, respectively.

The paper proceeds as follows. In Section II we discuss theoretical issues that are important for how well estimates from two-generation studies can be used to infer long-run social mobility. In Section III, we introduce the data set, discuss the construction of variables, and provide some descriptive statistics of the variables used in this study. In Section IV, we present the results of descriptive estimations of the association of the outcomes of children with those of parents, grandparents (income and education), and great-grandparents (education). In Section V, we try to disentangle mechanisms. Section VI concludes the paper.

II. Measuring Long-Term Intergenerational Mobility

A natural point of departure for measuring long-term intergenerational mobility in social status is to define when estimates from the simple AR(1) model can be used for extrapolations beyond two generations. This is discussed in some recent papers by Clark (2012), Clark and Cummins (2012), Solon (2013), and Stuhler (2013).[5] This can be done only under very strong conditions about the underlying transmission model and only with error-free data on the outcome of interest. Consider a stylized Becker-Tomes model, formally

(1) $y_t = \phi y_{t-1} + \tau e_t + u_t,$

(2) $e_t = \lambda e_{t-1} + \upsilon_t,$

where y is income (or education), e is endowment, ε and υ are random error terms, and t denotes generation. Stuhler (2013) shows that the extrapolation error—that is, the difference between the extrapolated long-run persistence and true long-run persistence, is 0 only if either $\tau = 0$ or $\lambda = 0$. Hence, it is required that income is an AR(1),

5. See also the theoretical work by Nybom and Stuhler (2013) that studies the impact on social mobility of future generations from structural changes affecting the current level of social mobility.

either with a serially correlated endowment term that is uncorrelated with parents' income, or with a serially uncorrelated endowment term that might be correlated with parents' income. Otherwise, actual long-run mobility will be different than what is predicted from an estimate using two generations of data.

Let us briefly discuss some important reasons for why researchers may have wrongly inferred long-run intergenerational mobility from studies on microdata covering two generations only.

A. Direct influences of the grandparent generation[6]

Mare (2011) discusses several ways for grandparents to invest in the human capital of their grandchildren. In addition, as noted by Solon (2013), grandparents often take an active part in the upbringing of their grandchildren. This means that they will transmit cultural influences partly independently of the parent generation. Furthermore, Solon (2013) points out that it is quite conceivable, although not fully understood, that genetic inheritance is more complicated than a simple AR(1) process across generations. Incorporating a positive direct effect of grandparents' traits in the above modeling framework tends to generate a slower than geometric decline in intergenerational persistence, hence an overestimate of long-run mobility using predictions from data on two generations (Solon 2013, Stuhler 2013).[7]

B. Poor measures of long-term social status

The role of "market luck" as a determinant of an individual's position in the distribution of life success is brought forth in Clark (2012) as an important reason for why long-run mobility is vastly overstated in two-generation studies. Clark postulates that in each generation, individual social status (x_t) is linearly related to the latent family (or dynasty) status (x_{t-1}), that is

$$(3) \quad x_t = \alpha + bx_{t-1} + e_t,$$

where e_t is an iid random error. However, social status is a latent variable that cannot be directly observed but, in each generation, is observed with a random error, that is

$$(4) \quad y_t = x_t + v_t,$$

where v_t is iid.

There are two reasons why the observed outcome variable in generation t (y_t) is only an imperfect measure of the underlying latent variable capturing family status in the same generation. If the outcome variable under study is labor earnings, this variable can be affected by "market luck" and the fact that people can choose occupations with similar status levels, such as philosophy professor and finance executive, with vastly different pecuniary compensations.[8]

6. This source of bias was recognized already in Becker and Tomes (1979, p. 1172).

7. Solon (2013) also develops an extension of the Becker-Tomes model where the endowment equation has a longer backward memory than only one generation.

8. It is explicitly shown in Stuhler (2013) that the higher the role of market luck the larger the extrapolation error.

As emphasized in Clark (2012), the relation between long-run intergenerational mobility and what we can estimate in autoregressive models with observable data n generations apart, that is, $y_t = \alpha + \beta_n y_{t-n} + e_t$, is:

$$(5)\quad E(\beta_n) = \frac{1}{1 + (\sigma_v^2 / \sigma_x^2)} b^n = \theta b^n.$$

It is easily seen that if we use estimates from two AR(1) models with data from consecutive generations to predict intergenerational persistence two generations apart by using the square of the estimated coefficient ($(\theta b)^2$), it will differ by a factor θ from the corresponding estimates when we use data two generations apart (θb^2).

There are at least two ways of recovering the underlying b parameter for long-term intergenerational mobility in social status. First, calibrate the parameter value that can rationalize the differences from estimates on consecutive data and those made on generations further apart. This is done in Clark (2012) on the estimates reported in a working paper version of this paper (Lindahl et al. 2011). Second, use the outcome from the grandparent generation as an instrumental variable. Note that the Clark model has a memory of only two generations. This means that the observable human capital outcome of the grandparent generation fulfills the exclusion restriction under the assumption that the model applies. In Section V1, we discuss the results of Clark (2012) and report IV estimates of long-term social mobility.[9]

C. A two-factor model and multidimensional endowments

An obvious violation of the conditions from Stuhler (2013) stated above is when both $\tau \neq 0$ and $\lambda \neq 0$ —that is, when there is more than one factor that is transmitted between generations. It is shown already in the canonical references Becker and Tomes (1979 and 1986) that average long-term mobility is slower when there are two sources of mobility with different persistence.

One specific example (discussed in Solon 2013 and Stuhler 2013) is if, in the stylized Becker-Tomes model, $\phi > \lambda$, so that the impact of parental income on the income of the child is large (perhaps because credit constraints are very important) whereas the endowment transmission across generations is small. In this case, we would, however, expect an extrapolation using two generations of data to *underestimate* long-run mobility. As shown in Stuhler (2013), the higher (lower) is the value of ϕ relative to λ, the more likely we are to under (over) estimate long-run mobility using extrapolation from data on two generations.

Endowments can also be multidimensional in nature. Stuhler (2013) shows that in a model where $\phi = 0$, but where there are two types of endowments (for instance, cognitive and noncognitive) that are transmitted differentially across generations, long-run social mobility will be slower than predicted by an AR(1) model.

9. Although their focus is not on multigenerational mobility, Solon (1992) and Zimmerman (1992) are two early attempts to correct for measurement error in fathers' earnings in studies of intergenerational mobility in earnings. Both these papers also use IV approaches for this purpose, Solon (1992) using fathers' education as an instrument for father's earnings, arguing that this leads to an upper-bound estimate, and Zimmerman (1992), which used a socioeconomic index as an instrument for father's education. Both papers found such measurement error correction procedures to generate estimates of much higher persistence.

D. Distributional changes across generations.

Another source of bias resulting from extrapolating from a simple AR(1) specification, related to the omitted variable case, is the presence of nonlinearities and/or changes in the shape of the distribution of the outcomes across generations.[10] The direction of the bias from this form of misspecification cannot be determined a priori. In this paper, we therefore report extrapolation results from regression coefficient estimates as well as correlation coefficients.

III. Data and Descriptive Statistics

The data set originally stems from the so-called Malmö Study (GEMS – Generations Emanating from the Malmö Study), a survey initiated in 1938 by a team of Swedish educational researchers.[11] *All* pupils attending third grade, normally at the age of ten and born in 1928 in any school in the Malmö metropolitan area (n = 1,542), were part of the original survey and constitute the index generation. It is important to stress that the survey did not only include the city area but also the surroundings including agricultural districts. Because the original study was not restricted to a particular characteristic of the children or the neighborhood, and all children in third grade were included in the survey, the sample is highly representative and in fact includes most of the individuals born in 1928 and living in Malmö at the age of ten.[12]

The original purpose of the Malmö Study was to analyze the correlation between social surroundings and cognitive ability. Hence, a host of family background information was collected, including parental earnings for several years and detailed information on the father's occupation. Over the years, the Malmö Study has been extended with information from both several rounds of followup surveys and register data.[13]

For the purpose of this study, we have extended the data in several ways. First, we have added parish register information on date of birth and death of the parents of the index generation. These parents constitute the first generation and were born between 1865 and 1912. Second, we have added register information on the second (index) generation's earnings histories and educational attainments. Third, we have obtained the same information on the spouses of the second generation. Fourth, we have obtained similar register information on the children of the second generation—that is, the third generation and their spouses. Finally, we have obtained register data on their children, the fourth generation in the data.

The resulting data set consists of information on up to four generations of the same

10. We thank a referee for pointing this out.

11. The material was originally collected by Siver Hallgren and developed by Torsten Husén. Hallgren (1939) is the first study published using this data set. See also de Wolff and Slijp (1973) and Palme and Sandgren (2008) for further description of the Malmö study data set.

12. Appendix 1 provides a short historical account of the development in Malmö and Sweden, focusing on the evolvement of institutions of likely importance for intergenerational mobility and the welfare state in Sweden during the relevant time period.

13. In 1993, 38 percent of the third and fourth generations still lived in Malmö, an additional 31 percent lived elsewhere in the county of Skåne, which is where Malmö is situated, 8 percent lived in the county of Stockholm, and the rest were quite evenly spread out in the rest of Sweden.

families, where the great-grandparents were typically born in the late 19th century and where the great-grandchildren typically finished their education in the early 21st century.

Figure 1 shows the number of observations by gender and whether or not they are related to the individuals in the original data set or included as a spouse, as well as the spread in the year of birth for each category. The average birth year for the first generation (G1) is 1891; the second (index) generation (G2) 1928; the third (G3) 1956; and, finally, the fourth generation (G4), the grandchildren of the index generation, 1985.

A. Data on Educational Attainment

There is no direct information on educational attainments for the first generation. However, since at the time educational attainments were closely linked to occupation, and the 1938 survey contains detailed information on occupational status, the educational scientists who originally obtained the data were able to construct a measure of educational attainments by assigning an education level corresponding to the educational requirements for each occupation. There are no education classifications available for the mothers of the index generation.

For the second to fourth generations, we have obtained data on educational attainments from the national education register. We mainly use information from 1985 for the second generation and from 2009 for the third and fourth generations. We transform the educational level measure for all generations into years of schooling based on the required number of years that must be completed for each level.[14]

In order to avoid the problem that some individuals in the youngest generation may have still been in school at the time of the most recent data collection, we restrict the analysis of years of education to individuals who were at least 25 years of age in 2009, hence excluding those born after 1984. So as to further increase the sample size for the analysis of education transmission, we construct a measure of whether or not an individual has completed an academic track in high school. This is a strong predictor of whether the individual continues on to higher education. We are then able to include children born until 1990. This increases the sample of family dynasties with educational data for four generations by about 35 percent.

B. Measures of Lifetime Earnings

Detailed earnings information allows us to construct measures of lifetime earnings for men in the first three generations. The fourth generation is not included in the analysis of earnings transmission because a large fraction of these individuals are too young to al-

14. With detailed information on completed level of education, we construct years of schooling as follows: seven for (old) primary school, nine for (new) compulsory schooling, 9.5 for (old) postprimary school (*realskola*), 11 for short high school, 12 for long high school, 14 for short university, 15.5 for long university, and 19 for a PhD. For those few individuals in the second generation where registry information for 1985 is missing, we use survey information from 1964. The education information from 1964 is in six levels and probably of lower quality than for 1985 or 2009. The conversion is done by imputing years of schooling by regressing the years of schooling variable in 1985 on indicators for 1964 using all individuals for whom educational information is available in both years. For individuals in the third generation with missing education data, we instead draw on registry information from 2005 and 1985.

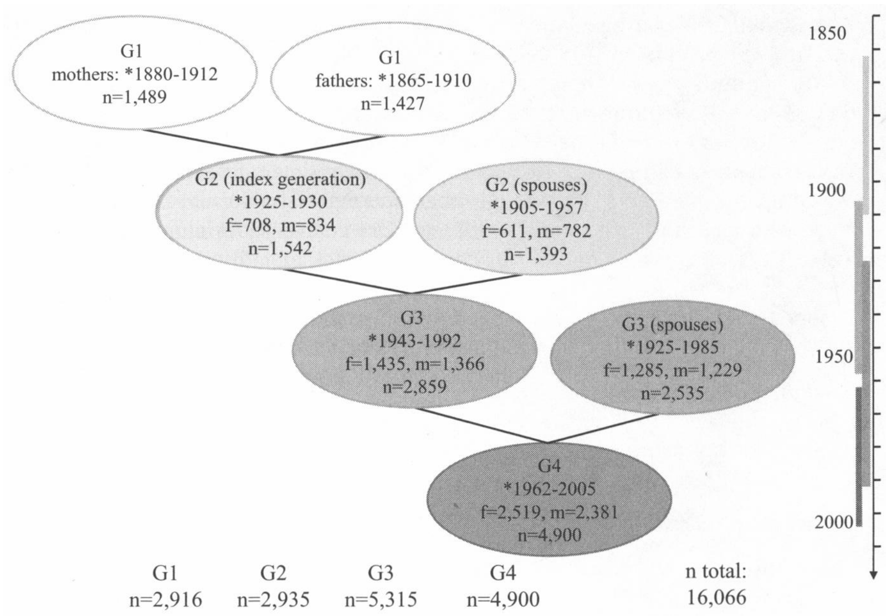

Figure 1
Overview of the GEMS database.
Notes: * = year of birth; *n* = number of individuals; *f* = female; *m* = male.
The vertical axis on the righthand side shows the spread in birth year for all four generations.

low the construction of meaningful measures of lifetime earnings. Although the amount of earnings information differs across generations, available data from local and national tax registers cover the most important years of working life for all three generations.

As regards the first generation, on average born in 1896, we have annual income for the years 1929, 1933, 1937, 1938, and 1942. This implies that income is typically observed between ages 33–46. Data for 1929, 1933, and 1938 were collected at the time of the original survey from local tax registers. Data for the years 1937 and 1942 were collected later, also from the local tax registers. The income measure is the sum of capital and labor income.

The second generation, most of which was born in 1928 (the original Malmö population) or around 1928 (the spouses of the Malmö children), is covered from the age of 20 by at least 15 observations of annual earnings. The first observations of labor earnings stem from 1948. Between 1948 and 1968, information on earnings is obtained manually from local tax registers for every fifth year. For individuals in the second generation who were not part of the original sample—that is, the other parent of the third generation individuals—we have earnings information between 1948 and 1968 to the extent that they cohabited with the individual from the original sample during that period or starting from 1968 if they did not. Between 1968 and 1984, information on earnings is obtained every third or fifth year from the national tax register. After

1984 and until 2008, we have information on annual earnings for each year, also obtained from the national tax register.

As for the third generation, typically born in the mid-1950s, earnings data start in 1968 and are collected from national tax registers. Like the second generation, information on earnings was collected every third or fifth year until 1984, after which there are annual observations up to 2008.

We compute our earnings measure for each generation in two steps. First, using all earnings data available,[15] we regress log-earnings on a cubic polynomial in *age* (= year-birth year) as well as year dummies, that is[16]

$$(6)\quad \log(earnings)_{it} = \alpha + \gamma_1 age_{it} + \gamma_2 age_{it}^2 + \gamma_3 age_{it}^3 + \sum_t \pi_t year_{it} + \varepsilon_{it}.$$

Second, we obtain the residual for each individual-year cell *it*, and then compute the mean residual for each individual—that is, the stable part of individual earnings, which is used as a measure of lifetime earnings.

C. Descriptive Statistics

We have information on educational attainments for 901 complete family dynasties—that is, with data available on at least one individual in each generation for four consecutive generations.[17] For earnings, there are 774 families with earnings information available for at least one male member of the family dynasty in three consecutive generations.

The GEMS data originally consisted of 1,542 unique individuals in the index generation (the second generation). Restricting the sample to those with fathers in the first generation and children in the third generation, 1,217 of those second generation individuals remain. If we further restrict the sample to those in the index generation who have grandchildren in the fourth generation (born no later than 2004), the sample shrinks to 1,092 individuals. Requiring the grandchildren to be born no later than 1990 (as we do when we look at academic high school track as an outcome for the fourth generation) restricts the sample to 971 individuals. Further requiring all four generations to have information on education generates the final sample of 905 individuals. Because of four twin pairs in the index generation, this amounts to 901 unique dynasties. Hence, the main reason for attrition of families is that the individual has no children.

Because earnings data are less informative, if available at all, for women in the ear-

15. We include all years for which we observe positive earnings, but exclude the observations when the individual was very young: below 19 years of age for the first generation, below 23 for the second, and below 27 for the third.

16. This approach is not valid in the presence of life-cycle bias (see Haider and Solon 2006; Böhlmark and Lindquist 2006). However, because we have access to reasonable lifetime income measures for both parents and children, life-cycle bias should not be an issue here.

17. We have 901 complete families, or dynasties, with four generations when we include fourth generation children born until 1990. For this sample, the education measure used for the fourth generation is academic high school track. In order to obtain a meaningful measure of years of education for the fourth generation, we restrict the analysis to children born before 1985, resulting in 673 complete families.

lier years, we restrict the analysis of earnings associations to sons, fathers, and grandfathers. Note that for roughly half of the earnings sample, the male family member in the second generation (the father) is not the biological son of the male member of the family dynasty in the first generation (the grandfather), but is instead the son-in-law. This almost doubles the earnings sample.[18] Of the 1,526 fathers in the first generation, 881 remain if we allow for both sons and son-in laws for the second and third generation to be linked. If we further require the men for these three generations to have earnings data, 774 men in the first generation remain. Hence, we only lose about 12 percent of our sample due to missing earnings information.

Table 1 reports descriptive statistics by generation and gender for the samples used in this study. We show statistics corresponding to the individuals in our estimation sample for education (four generations separated by gender) and earnings (three generations of men). The first column shows means and standard deviations for the fathers of the children in the index generation (Generation 2). These 901 great-grandfathers were on average born in 1896 and had 7.3 years of schooling. We observe 773 men with earnings information in the first generation. The number of unique men in the first generation differs from the number of observations reported in Column 1 (and hence from the number of dynasties) because (1) there are four (two) twin pairs in the index generation in the education (earnings) samples, and (2) since for earnings we do not require the father and child to be biologically related, there are some additional nonbiological siblings of children in the index generation added to this sample.

The next two columns show descriptive statistics for those in the second generation (first interviewed in 1938 and typically born in 1928) as well as mothers and fathers of the children in the third generation. Among these grandparents, typically born in 1928, there are 470 men who acquired 10.2 years of schooling and 435 women who on average acquired 9.5 years. The third column shows descriptive statistics for those in the third generation. The parents of the children in the last generation were, on average, born in 1955 and have, on average, acquired just over 12 years of schooling. The earnings figures for men in the second and third generations pertain to sons and grandsons of the first generation of men as well as the male spouse of the daughters and granddaughters belonging to the index and the next generations. There are 787 unique fathers in the index generation with earnings data used as 1,174 observations.

The last two columns show descriptive statistics for the descendants of the three earlier generations who are old enough to be included in the regressions: 27 years of age in 2008 for earnings regressions; 25 years of age in 2009 for education estimations; and, finally, 19 years of age for the academic high school track regressions. These children were, on average, born in 1981, and 55 percent of the women and 44 percent of the men have attended an academic high school track. The children born before 1985 have on average acquired 13.0 (women) or 12.4 (men) years of schooling.

The average residual of log earnings, with means and standard deviations reported

18. This approach is supported by results in Chadwick and Solon (2002) for the United States and Holmlund (2006) for Sweden. Both find that assortative mating is strong enough to generate quite similar intergenerational elasticities between parents' earnings and the offspring as for the spouse of the offspring. As a check, we also estimated transmission coefficients for education including spouses of offspring. The estimates are then very similar to those using only individuals who are biologically related across the four generations (which are the estimates reported in Table 2).

Table 1
Descriptive Statistics

Variable	Generation 1 (Great-Grandparents)	Generation 2 (Grandparents)		Generation 3 (Parents)		Generation 4 (Children)	
	Great-Grandfather 1	Grandmother 3	Grandfather 4	Mother 5	Father 6	Daughter 7	Son 8
Years of schooling	7.30	9.53	10.15	12.05	12.11	12.95	12.42
	(1.60)	(2.67)	(2.96)	(2.47)	(2.59)	(1.98)	(2.13)
	[5,14]	[7,19]	[7,20]	[7,20]	[7,20]	[7,20]	[7,20]
Academic high school track						0.55	0.44
						(0.50)	(0.50)
						[0,1]	[0,1]
Earnings (expressed in 2010 prices)	92,264		288,767		350,472		
	(144,129)		(208,924)		(344,194)		
	(year 1933)		(year 1968)		(year 2000)		
Average residual log earnings	−0.047		−0.018		−0.121		
	(0.529)		(0.637)		(0.763)		
	[−1.74,2.76]		[−2.71,2.26]		[−4.11,1.90]		
Year of birth (education)	1896.12	1927.91	1927.87	1954.67	1954.53	1981.45	1981.49
	(7.20)	(0.40)	(0.40)	(4.90)	(4.46)	(6.30)	(6.35)
	[1859, 1910]	[1925, 1930]	[1926, 1929]	[1944, 1970]	[1943, 1969]	[1962, 1990]	[1962, 1990]
Year of birth (earnings)	1895.70		1926.73		1956.69		
	(7.48)		(3.27)		(5.54)		
	[1865, 1910]		[1888, 1947]		[1943, 1981]		
Number of observations (education)	905	435	470	831	722	1,451	1,548
Number of observations (earnings)	803		1,174		1,174		

Notes: The first figure in each cell is the mean of the variable. The figure in parenthesis is the standard deviation and the figures in square brackets are minimum and maximum values, respectively. The education statistics are calculated for the observations used in Table 2 and the earnings statistics are calculated for the observations used in Table 4. The statistics for years of schooling for Generation 4 are calculated for those born before 1985 (887 daughters and 936 sons).

in the third row, summarizes the earnings measure actually used in the estimations.[19] We also report annual earnings in 2010 prices that demonstrate the growth in earnings seen in Malmö over the almost 70 years from the mid-1930s to 2000.

D. Similarity Between the Third and Fourth Generation of the GEMS and Sweden's Population

Because our data do not originate from a random sample of the Swedish population, a key question for the external validity of our results is to what extent our sample of families is comparable to a random sample of the population as regards the distribution of education and earnings.

We investigate this issue by comparing the economic situation of the families in our sample to families living in Sweden in the 1930s. We compare the earnings distribution for our first generation with the earnings distribution for the entire population by means of Lorenz curves based on the estimates of the Swedish earnings distribution obtained by Bentzel (1952) from tax-registry data. Figure A1 shows estimates of Lorenz curves based on the earnings distribution of the first generation in our data in 1937 with those obtained by Bentzel for the years 1935 and 1945, respectively. The results suggest that the income distribution among the original Malmö families is very similar to the national income distribution.

We also investigate the descendants of the original sample. If the third and fourth generations of the GEMS population are still comparable to random samples of the Swedish population, we would argue that conclusions based on our estimates have something to say about 20th century intergenerational mobility in Sweden and not only for the Malmö sample under study. Indeed, Tables A1 and A2 show that the distribution of educational attainments and earnings is remarkably similar for the GEMS data compared to samples of the Swedish population that mimic the age structure of younger generations of Malmö data.

IV. Results

A. Intergenerational Persistence in Educational Attainments

Table 2 shows the first set of results: the estimated transmission coefficients for education across the four generations under study. All estimates are results from the bivariate regression model

$$(7) \quad y_{it} = a + by_{it-j} + d'x_i + u_{it},$$

where $j \geq 1$, y_t is the outcome of the child and y_{t-j} is the outcome of the parent ($j = 1$), grandparent ($j = 2$) or great-grandparent ($j = 3$), where i indicates the child. x_i is a vec-

19. As described in Section IIIB, we compute the log-earnings residuals in two steps: First, we stack all observations (individuals*years with available earnings data > 0) and predict residuals for each individual-year cell *it*. Second, we compute the mean residual for each individual. Hence, the standardization is done on individual-year cells whereas the mean residuals shown in Table 1 are the average residuals over individuals. The means are negative because individuals differ in the number of years for which they have available earnings data and because those with fewer years of earnings data have lower earnings.

Table 2
Estimates Persistence in Educational Attainments Across Generations

	Years of Schooling Great-Grandparent 1	Years of Schooling Grandparent 2	Years of Schooling Parent 3
Years of schooling – grandparent	0.607***		
	(0.065)		
	[0.334]		
	$N = 905$		
Years of schooling – parent	0.375***	0.281***	
	(0.043)	(0.024)	
	[0.229]	[0.312]	
	$N = 1,553$	$N = 1,553$	
Prediction	0.171		
Standard error for prediction	(0.024)		
t-statistic for difference	4.14		
Years of schooling – child	0.145***	0.131***	0.296***
	(0.046)	(0.023)	(0.021)
	[0.123]	[0.202]	[0.412]
	$N = 1,823$	$N = 1,823$	$N = 1,823$
Prediction	0.050	0.083	
Standard errors for predictions	(0.010)	(0.009)	
t-statistic for difference	2.01	1.94	
Academic high school track	0.032***	0.028***	0.066***
(= 1) – child	(0.007)	(0.004)	(0.004)
	[0.104]	[0.163]	[0.343]
	$N = 2,999$	$N = 2,999$	$N = 2,999$

Notes: Each reported estimate is from a separate regression of the education of members of one generation on the education of members of an older generation. All regressions control for a quadratic polynomial in birth years of both generations. The reported standard errors (in parentheses) are clustered on families. Standardized estimates are reported in brackets.

tor of controls including a cubic in birth year and a gender dummy for generation t, and a cubic in birth year and a gender dummy for generation t-j. As many members of the last generation had not yet completed their education at the date of data collection, we use completion of an academic track in secondary school as a proxy for educational aspiration. The last row in Table 2 reports linear probability model estimates of the relation between the probability of having completed an academic high school track and earlier generations' educational attainments measured in years of education. The estimates (standard errors) are outcomes from regressions using unstandardized variables. Estimates from regressions using variables that have been standardized to have mean zero and standard deviation one in each generation are reported in square brackets.

Table 1 also includes predictions of intergenerational persistence between generations two or three generations apart based on the AR(1) estimates from consecutive generations. The standard errors for the predictions are reported in square brackets below the point estimates. These standard errors are obtained by using the Delta method.[20] Test statistics from a simple *t*-test for equality between the predictions and the corresponding direct estimates were obtained using the bootstrap procedure and are reported below the standard error estimates.

Table 1 reveals several interesting results. First, there is a statistically significant estimate for the association between great-grandfathers' educational attainment and that of great-grandchildren. This result shows that there is a persistent correlation despite the fact that there are two generations, or on average 75 years, between the births of these generations. Second, the association between educational outcomes of the great-grandparent generation and the child generation, as well as between the great-grandparent generation and the parent generation, is stronger than what would be expected if we were to predict these correlations based on the correlation between the adjacent generations involved.

The point estimates suggest that the differences are quite large. The estimated direct association of 0.375 between the great-grandparent and the parent generations is more than twice as large as the prediction of 0.171 (0.607 x 0.281) based on the conventional AR(1) estimates and 0.145 between the great-grandparent and the child generations is almost three times larger than the prediction of 0.050 (0.607 x 0.281 x 0.296). We can reject the hypothesis of equality between the predictions and the direct estimates for the generations two or three generations apart. In the third case, for the grandparent and child generations, we get a *t*-statistics on 1.94, which gives a *p*-value of 0.055.

Over the studied generations, it is well known that in Sweden as elsewhere, the education distribution has changed dramatically as education has expanded from a mean of seven years of schooling in the first generation to almost 13 in the fourth generation. In Table 1, we therefore also report standardized estimates (correlation coefficients) in square brackets. Interestingly, these estimates suggest that much of the decline in the intergenerational education persistence between the first two and the second two generations from 0.607 to 0.281 is, in fact, due to changes in the education distribution. The standardized estimates are instead rather stable over time. However, also for these standardized estimates we are able to reject that the predicted relation between the first and the third generation is the same as the estimated standardized coefficient.[21]

In Table 1, we reported estimates based on data including both men and women. This would be problematic if intergenerational transmission of education was very different for daughters and sons and from mothers and fathers. In Table A3, we provide reassuring support for pooling. The table reports the results from estimations of the intergenerational transmission coefficients separately by gender of offspring and ancestor. The finding is that the intergenerational correlation in educational attainments seems to be independent of the gender of both ancestor and offspring. For example,

20. The approximation of the variance for the product of β_1 and β_2, where β_1 is the estimate between generation one and two and β_2 is the estimate between generation two and three based on the Delta method (see Greene 2003), is $\beta_2^2\sigma_{\beta_1}^2 + \beta_1^2\sigma_{\beta_2}^2 + 2\beta_1\beta_2\sigma_{\beta_1\beta_2}$. We used the bootstrap method to obtain estimates of the covariance term, $\sigma_{\beta_1\beta_2}$.

21. If we do the same exercise for the third and fourth generation we can also reject that the predicted association, which is almost 60 percent higher, is the same as the estimated association.

the correlation between the first and third generations is almost the same for males and females in the third generation.

We can also infer the representativeness of our results by comparing some of the reported estimates to corresponding estimates based on large random samples of the Swedish population. If we compare the estimates from using parents and children (that is, for the third and fourth generation) in this Malmö sample to estimates based on a random sample of Swedish parents born 1943–55 (Holmlund et al. 2011), the estimates presented in this paper are only slightly higher.

Changes in education distributions affect not only estimates of intergenerational transmission but may also alter the meaning of a particular number of years of education over time. It is also possible that there are nonlinearities in the transmission process that are not fully captured in the linearly estimated transmission coefficients. Therefore, we compute intergenerational transmission probabilities across education categories. The corresponding odds ratios and marginal distributions are reported in Table 3. For each generation, we define four levels of education, from compulsory to university education.

First, note that the education distribution in the first generation is very skewed. The vast majority (85 percent) of the ancestors have the lowest level of education, which at the time was six or seven years. In the first generation, it is not even meaningful to single out university educated: Only about 3 percent have secondary education or more. Already among their children, more than half are educated beyond the compulsory level. In the fourth generation, only 10 percent have compulsory schooling as their highest educational attainment.

Odds ratios for education transitions confirm the main result from Table 1 — namely that there is a substantial persistence across generations in the education level attained. In particular, the third panel of Table 3 shows that there is a substantially higher probability that an individual has a university degree if the ancestor, three generations before, was educated beyond the compulsory level. In addition, these odds ratios indicate a presence of nonlinearities: There is higher persistence — that is, odds ratios are above one — at the upper end of the education distribution. In particular, between the first and the second generation, having parents with education beyond the compulsory level makes offspring between two and over six times more likely to have a university degree as compared to random assignment, while there is only a small excess odds ratio to remain in the lowest education category if the parents have only compulsory education. This pattern also persists across several generations. We can see that ancestors with more than compulsory education in the first generation are, on average compared to random assignment, between 49 and 67 percent more likely to have university educated great-grandchildren, whereas those with only compulsory schooling are only 3 percent more likely than random assignment to have great-grandchildren with compulsory schooling.

B. Intergenerational Persistence in Earnings

Table 4 shows the estimates of intergenerational earnings mobility between the first and second generations, the second and third generations as well as between the first and third generations, respectively. Although Swedish society has undergone profound and important changes in different dimensions between the most active period of the

Table 3

Educational Attainment of Ancestor in the First Generation and Odds Ratios for the Educational Attainment of Offspring in Generations 2, 3, and 4

Education of Ancestor in Generation 1		Education of Offspring: Compulsory	Compulsory +	High School	University	$P_{\cdot i}$	Observation_i
		Education of Generation 2					
Compulsory	$P_{1j}/P_{\cdot j}$	1.12	1.01	0.86	0.54	0.85	765
Compulsory+vocational	$P_{2j}/P_{\cdot j}$	0.50	0.99	1.85	2.19	0.08	75
Compulsory+ academic	$P_{3j}/P_{\cdot j}$	0.18	1.04	1.79	4.08	0.04	37
High school/university	$P_{4j}/P_{\cdot j}$	0.24	0.58	1.51	6.37	0.03	29
All	$P_{\cdot j}$	0.45	0.31	0.17	0.07	1.00	
	$\text{Obs}_{\cdot j}$	408	281	150	66		905
		Education of Generation 3					
Compulsory	$P_{1j}/P_{\cdot j}$	1.08	1.09	0.98	0.79	0.85	1,317
Compulsory+vocational	$P_{2j}/P_{\cdot j}$	0.69	0.64	1.11	1.84	0.08	128
Compulsory+ academic	$P_{3j}/P_{\cdot j}$	0.55	0.41	1.24	2.23	0.04	60
High school/university	$P_{4j}/P_{\cdot j}$	0.12	0.34	1.09	3.01	0.03	48
All	$P_{\cdot j}$	0.18	0.37	0.27	0.19	1.00	
	$\text{Obs}_{\cdot j}$	280	567	416	290		1,553
		Education of Generation 4					
Compulsory	$P_{1j}/P_{\cdot j}$	1.03	1.05	1.01	0.93	0.85	1,620
Compulsory+vocational	$P_{2j}/P_{\cdot j}$	0.93	0.43	0.94	1.49	0.08	121
Compulsory+academic	$P_{3j}/P_{\cdot j}$	0.43	0.82	0.82	1.67	0.04	47
High school/university	$P_{4j}/P_{\cdot j}$	0.58	0.74	0.87	1.57	0.03	35
All	$P_{\cdot j}$	0.10	0.16	0.49	0.25	1.00	
	$\text{Obs}_{\cdot j}$	179	283	897	464		1,823

Notes: Education Generation 1: compulsory maximum eight years, postcompulsory: vocational nine years, postcompulsory: academic (*Realskola*) ten years, high school or university: minimum 12 years. Education Generations 2–4: compulsory maximum nine years, postcompulsory: short academic or vocational high school track (*Realskola* or short high school track) 10–11 years, academic high school track 12–14 years, university: minimum 15 years.

Table 4
Estimates of Persistence in Earnings Across Generations: Log Earnings of Male Offspring Regressed on Log Earnings of Male Ancestor

	Ancestor	
Offspring	Grandparent Generation 1	Parent Generation 2
Log(earnings) – parent Generation 2	0.356***	
	(0.040)	
	[0.307]	
	$N = 803$	
Log(earnings) – child Generation 3	0.184***	0.303***
	(0.044)	(0.043)
	[0.141]	[0.268]
	$N = 1{,}174$	$N = 1{,}174$
Prediction	0.108	
Standard error	(0.020)	
t-statistic for difference	1.58	

Notes: Each reported estimate is from a separate regression of the son's residual log earnings on residual log earnings of the ancestor. The earnings measures are average residual log earnings from a regression of log earnings on a cubic polynomial in birth years and year dummies (see Section II). The reported standard errors (in parentheses) are clustered on families. Standardized estimates are reported in brackets.

first generation born around 1900 and the third generation mostly born in the 1950s and 1960s, the elasticities in earnings between consecutive generations seem to be quite stable: 0.356 between the first and second generations and 0.303 between the second and third. The latter elasticity is only slightly larger as compared to estimates from previous Swedish studies of the same time period using random samples of the entire population (see Björklund et al. 2006).

The results in Table 4 allow us to predict the earnings mobility between the first and third generations from the two two-generation mobility measures. This gives us a prediction of 0.108, which is substantially lower than the estimate of 0.184 obtained from data. However, a t-test of equality between the predicted and the estimated three-generation mobility measure gives a t-statistic of 1.58, indicating an only marginally significant difference.[22]

As in the case of education, it is interesting to explore whether our linear summary measures hide nonlinearities in the transmission of earnings across generations. We examine this by means of transition matrices. Table 5 shows transition matrices for income quintiles across generations. The first panel reports the transition probabilities between the first and the second generations; the second panel reports the correspond-

22. We use the method described in Footnote 20 to obtain a standard error for the prediction and the bootstrap procedure to obtain the t-statistics for the test of difference between predicted and actual intergenerational persistence across three generations.

Table 5
Transition Matrices: Offspring Earnings Quintile Conditional on Ancestor's Earnings Quintile

Earnings Quintile of Ancestor	Earnings Quintile of Offspring				
	Grandfather Generation 2				
Great-grandfather Generation 1	Q1	Q2	Q3	Q4	Q5
Q1	0.30	0.29	0.21	0.11	0.10
Q2	0.25	0.20	0.20	0.23	0.11
Q3	0.16	0.20	0.26	0.22	0.17
Q4	0.16	0.18	0.21	0.27	0.18
Q5	0.14	0.14	0.11	0.18	0.44
	Father Generation 3				
Grandfather Generation 2	Q1	Q2	Q3	Q4	Q5
Q1	0.31	0.26	0.17	0.18	0.09
Q2	0.20	0.24	0.19	0.20	0.18
Q3	0.21	0.18	0.28	0.18	0.15
Q4	0.15	0.18	0.22	0.22	0.23
Q5	0.14	0.15	0.14	0.23	0.35
	Father Generation 3				
Great-grandfather Generation 1	Q1	Q2	Q3	Q4	Q5
Q1	0.19	0.23	0.21	0.24	0.14
Q2	0.23	0.22	0.23	0.17	0.14
Q3	0.25	0.19	0.20	0.20	0.16
Q4	0.17	0.20	0.21	0.20	0.22
Q5	0.16	0.16	0.16	0.18	0.34

Notes: Fathers and sons; 774 families.

ing figures for the second and third generations; finally, the third panel shows the transitions between the first and the third generations.

There is one result of particular interest revealed in Table 5. The persistence across two consecutive generations is higher at the higher end of the income distribution. The highest persistence in all of the three panels is found for the fifth quintile, that is, the top 20 percent of the earnings distribution. As many as 34 percent of the grandchildren of the individuals in the fifth quintile remain at the very top of the income distribution. Moreover, the persistence in this cell is almost as high when we compare grandfathers and grandsons (first and third generations) as when the grandsons are instead compared to their fathers (second and third generations).

If we briefly summarize the results from the descriptive estimations, they point toward a surprisingly strong association between grandparental education and earnings and education and earnings of grandchildren and between great-grandparental education and education of great-grandchildren. Hence, regression toward the mean takes longer in Sweden than what is suggested by the comparatively low estimates of intergenerational persistence found for two consecutive generations. In addition, transition matrices reveal that there is higher persistence at the upper end of the education and income distributions. We also find that simply taking the square of the intergenerational correlation does not give an accurate picture of what we find using children and grandparents, suggesting that the basic assumption that intergenerational transmission follows an AR(1) process does not hold.

V. Why Do We Find Evidence of Such High Long-Run Intergenerational Persistence?

As we discussed in Section II, there are several possibilities why the predictions of long-run mobility based on estimates using data for consecutive generations may overestimate true long-run social mobility. In this section, we will further examine two of these hypotheses: the latent variable model suggested by Clark (2012) and independent influences of the grandparent generation on the outcome of their grandchildren in an augmented (AR(2)) Galtonian model. Let us begin by investigating the first interpretation.

A. Estimates of Long-Term Social Mobility

On the basis of the model presented in Section II and our results on standardized intergenerational persistence in education and earnings presented in Tables 2 and 4, Clark (2012) calibrates the two-generation long-term intergenerational elasticities (*b*) corresponding to our estimates. Its estimates are 0.60 for educational attainments and 0.49 for earnings, which is about twice as large as our corresponding standardized estimates based on data for two consecutive generations.

As we concluded in Section II, the long-term intergenerational persistence in social status can also be recovered from a 2SLS model, using grandparental outcome (y_{t-2}) as an instrumental variable for the parental outcomes (y_{t-1}).[23] In the Clark model, the necessary exclusion restriction that the grandparental outcome (y_{t-2}) only affects child outcome indirectly through the influence on parents' outcome holds because the random deviations from the latent social status in each generation (v_t in Equation 4) is iid and hence serially uncorrelated across generations.[24]

Tables 6 and 7 show the OLS and 2SLS estimates for education and earnings, respectively. The first three columns of Table 6 show the results for years of schooling: the first column for Generations 2 and 3 and the next two columns for Generations 3

23. Halphen Boserup et al. (2013) uses a similar model when studying intergenerational persistence in wealth.

24. In Lindahl et al. (2014), using the same data set as in this paper, we apply a different IV strategy (using great-grandparents' education as an instrument for parents' education) to test a prediction of the Becker-Tomes model that grandparents' human capital should enter with a negative sign in a regression of child's human capital on the human capital of parents and grandparents. We do not find support for this prediction of the Becker-Tomes model.

Table 6
OLS and IV Regressions of Children's Education on Parents' Education

Dependent Variable:	Years of Schooling			Academic High School Track	
	Generation 3	Generation 4		Generation 4	
Main equation:	Education of child				
a) OLS					
Schooling of parent	0.281*** (0.024) [0.312] N = 1,553	0.296*** (0.021) [0.412] N = 1,823		0.066*** (0.004) [0.343] N = 2,999	
R^2	0.152	0.195		0.138	
b) IV					
Schooling of parent	0.524*** (0.076) [0.584] N = 1,553	0.504*** (0.067) [0.702] N = 1,823	0.473*** (0.063) [0.659] N = 1,823	0.102*** (0.013) [0.535] N = 2,999	0.097*** (0.012) [0.508] N = 2,999
R^2	0.087	0.138	0.154	0.106	0.114
F-test of excluded instruments in first-stage	220.52	197.12	47.56	368.26	83.56
Hausman test (t-statistics)	3.37	3.27	2.98	2.91	2.74
Instruments:					
Schooling of grandparents	Yes	Yes	Yes	Yes	Yes
Schooling of great-grandparents	No	No	Yes	No	Yes

Notes: Each reported estimate is from a separate regression of the education of members of the child generation on the education of the parent generation. All regressions control for a quadratic polynomial in birth years of both generations. The reported standard errors (in parentheses) are clustered on families. Standardized estimates are reported in brackets.

and 4. The last two columns show the results from a linear probability model in which the dependent variable is an indicator variable taking the value 1 if members of the fourth generation complete an academic high school track. For each outcome, we estimate two 2SLS specifications. The first specification uses the outcome of grandparents as an instrument for the outcome of parents. In the second specification, for education, we extend the set of instrumental variables to include great-grandparents' education in addition to grandparents' education. For earnings, we extend it by including grandparents' education in addition to grandparents' earnings.

Tables 6 and 7 also report t-statistics from a Hausman test. The null hypothesis for this test implies that parents' human capital outcomes are an adequate measure of their social status and hence, that θ in Equation 5 is close to 1. In this framework, it means that the two-generation OLS model gives an unbiased estimate of long-term intergen-

Table 7
OLS and IV Regressions of Children's Earnings on Parents' Earnings

Dependent Variable:	Residual Log Earnings	
	Generation 3	
Main equation:	Earnings of child	
a) OLS		
Earnings of parent	0.303***	
	(0.043)	
	[0.268]	
	N = 1,174	
R^2	0.064	
b) IV		
Earnings of parent	0.515***	0.537***
	(0.120)	(0.118)
	[0.456]	[0.475]
	N = 1,174	N = 1,147
R^2	0.033	0.010
F-test of excluded instruments in first-stage	122.54	29.74
Hausman test (t-statistics)	1.89	2.13
Instruments:		
Earnings of grandparents	Yes	Yes
Schooling of grandparents	No	Yes

Notes: Each reported estimate is from a separate regression of residual log earnings of members of the child generation on residual log earnings of the parent generation. The earnings measures are average residual log earnings from a regression of log earnings on a cubic polynomial in birth years and year dummies (see Section II). The reported standard errors (in parentheses) are clustered on families. Standardized estimates are reported in brackets.

erational mobility. Under the Clark model, the alternative hypothesis implies that only the IV estimate gives a consistent estimate of long-run mobility. However, rejecting the null hypothesis may also imply that the model is misspecified—that the exclusion restriction does not hold. This means that there is a *joint* alternative hypothesis with two alternatives: (a) long-term mobility is different from the coefficient recovered from OLS models estimated using data from two consecutive generations; (b) the exclusion restriction does not hold and grandparents' human capital outcomes have a direct influence on the outcomes of the child generation.

As can be seen in Tables 6 and 7, the 2SLS coefficient estimates are much larger than the corresponding OLS estimates. For years of schooling, the difference ranges between 60 percent and 86 percent depending on specification, and for earnings the difference ranges between 70 percent and 77 percent. The test statistics from Hausman tests show that we can reject that the IV and OLS models produce the same estimates, although the statistic is only marginally significant for the first column earnings estimates (p-value 6.0 percent).

Table 8
OLS Regressions of Children's Education on Parents' and Grandparents' Education

Dependent Variable:	Years of Schooling		Academic High School Track
	Generation 3	Generation 4	Generation 4
Main equation:	Education of child		
Schooling of parent	0.240***	0.266***	0.060***
	(0.027)	(0.023)	(0.004)
	[0.267]	[0.371]	[0.315]
Schooling of grandparent	0.180***	0.062***	0.011***
	(0.046)	(0.021)	(0.004)
	[0.110]	[0.096]	[0.069]
	N = 1,553	N = 1,823	N = 2,999
R^2	0.164	0.205	0.143

Notes: All regressions control for a quadratic polynomial in birth years for all three generations. The reported standard errors (in parentheses) are clustered on families. Standardized estimates are reported in brackets.

In summary, we can reject the null hypothesis that parents' human capital outcomes adequately capture long-run social status and that the traditional OLS model results in unbiased estimates of long-term intergenerational mobility. However, since we have a joint alternative hypothesis, the outstanding question is if the underlying reason is that the Clark model applies and that long-term mobility is indeed much smaller than suggested by two-generation studies and/or there is a direct influence of grandparental outcomes beyond the indirect effect through the parental generation. As we have a just-identified model, we are not able to test instrument validity and, therefore, we are not able to discriminate between these two hypotheses.

B. OLS Estimates of AR(2) Models

We estimate the following OLS model for intergenerational transmission of human capital:

$$(8)\quad y_{it} = a + b_1 y_{it-1} + b_2 y_{it-2} + d'x_i + u_{it},$$

where y_t is the outcome of the child, y_{t-1} is the outcome of the parent, and y_{t-2} is the outcome of the grandparent, where i indicates the child. x_i consists of a cubic polynomial in birth years and a gender dummy in each of the three generations considered.

Table 8 shows the estimates of Equation 8 when educational attainment is the measure of human capital. Table 9 shows the corresponding estimates for earnings. The first two columns in Table 8 show the results for years of schooling: Column 1 reports how outcomes in the third generation are associated with outcomes in Generations 2 and 1, and Column 2 reports how outcomes in the fourth generation are

Table 9
OLS Regressions of Sons' Log Earnings on the Log Earnings of Fathers' and Grandfathers' Education

Dependent Variable	Log(Earnings)-Child
Log(earnings) – parent	0.281***
	(0.045)
	[0.249]
Log(earnings) – grandparent	0.084*
	(0.044)
	[0.064]
	N = 1,174
R^2	0.067

Notes: The estimates are from a regression of the son's residual log earnings on the residual log earnings of the father and the grandfather. The earnings measures are average residual log earnings from a regression of log earnings on a cubic polynomial in birth years and year dummies (see Section II). The reported standard errors (in parentheses) are clustered on families. Standardized estimates are reported in brackets.

associated with outcomes in Generations 3 and 2. Column 3 shows the results from a linear probability model of how educational attainment in Generations 3 and 2 is related to the probability that members of the fourth generation complete an academic high school track. The intergenerational transmission of schooling estimates in the first row of Table 8 (which are conditional on grandparents' education) can be compared to the following unconditional estimates in Table 2: 0.281, 0.296, and 0.066, respectively.

The results for education show unambiguously that the estimated coefficients for the grandparent generation are significantly different from zero.[25] This is true also for the estimate on earnings data although the coefficient on grandparents' earnings is significant only at the 10 percent level.

Overall, the results show that there is an independent association between grandparents' human capital outcomes and the outcomes in the child generation in an AR(2) model. This implies that extrapolating from persistence estimates based on two consecutive generations underestimates the long-term intergenerational persistence due to omission of grandparents from the model.[26]

25. Note that if we estimate AR(3) models for education, the estimate for great-grandparents' schooling is insignificant (with a large standard error) and the estimates for parents' and grandparents' schooling are almost identical to those reported in the last two columns of Table 8.

26. This interpretation is supported by recent results in Adermon (2013). Using models with grandparents' fixed effects and a large random sample of Swedes, he finds that grandchildren born earlier, who are therefore more likely to have spent time with their grandparents, are more strongly affected by grandparents' educational attainment than younger grandchildren. It is also reassuring that Adermon's estimates without grandparents' fixed effects are, in fact, very similar to our estimates using AR(2) models. This supports the generalizability of our findings.

VI. Conclusions

We have shown that the persistence in educational attainments and earnings is much stronger across three generations than predicted from simple Galtonian regressions for two generations. For educational attainments we have shown that this also applies for four generations. These results are backed up with results from transition matrices, which also show that the persistence is strongest at the upper end of both the earnings and the educational distributions. They are further confirmed by an IV model and, finally, by an augmented Galtonian regression that includes outcomes from two, rather than one, generation of ancestors.

The intergenerational persistence is stronger for educational attainments than for earnings and, more interestingly, the difference between the two-generation Galtonian models and actual persistence is larger for educational attainments. A possible background to this result is that the choice of educational direction and level is more sensitive to family traditions and resources, dynastic human capital, while earnings are more sensitive to what Becker and Tomes (1979, 1986) label as "market luck."

Following the theoretical results obtained by Stuhler (2013) and in the framework of the Becker-Tomes model presented at the beginning of Section II, our results suggest that we can reject that the outcome of the child generation does *not* depend on parental endowments in addition to parental human capital outcomes. This result is very much in line with several recent studies on intergenerational mobility (see, for example, Holmlund et al. 2011 and Lefgren et al. 2012).

The most obvious implication of our results is that the inference on long-term persistence in human capital outcomes from the huge empirical literature on intergenerational mobility based on two-generation data should be interpreted with caution. Income inequality is certainly not "wiped out" in three generations, as suggested by Becker and Tomes (1986). However, such estimates can still be used for inference on shorter-term mobility.

Appendix 1

The City of Malmö

The four generations studied in this paper span a century during which Swedish society was transformed from early industrialization to present-day welfare society. Although subsidized childcare, generous child allowances, free schooling through high school, generous grants and loans for higher education, social security, unemployment benefits, free healthcare, and pensions constitute today's welfare system, at the beginning of the 20th century Malmö had some, but not all, of these institutions in place when the parents of the initially sampled index generation grew up.

Malmö is located in the southern part of Sweden. It was and is by population size Sweden's third city, after Stockholm and Gothenburg. At the beginning of the 20th century, Malmö grew at a rapid pace and tripled its population from 61,000 to 192,000 between 1900 and 1950, compared to today's 300,000. Much of the population growth was a result of rapid urbanization. Malmö was early on one of the most industrialized cities in Sweden while the surroundings of the city were and still are dominated by agriculture. When the original data collection of the Malmö study was initiated in 1938, three large employers dominated.[27] After 1960, an increasing fraction was employed within the public sector and by 1980, 20 percent of the men and 50 percent of the women held public sector jobs. Hence, the Malmö labor market has, like in most other cities, gradually been transformed to services.

In the early 20th century, Swedish compulsory schooling was only six years but a seventh year was introduced already in 1914 in Malmö. Yet, many children kept leaving school after six years. Seven years of schooling only become the norm around 1920 when a municipal grant was introduced to compensate poor families for the lost earnings during the seventh year of school. This grant existed until 1936 when compulsory schooling was extended to seven years throughout Sweden. In the late 1930s, almost a third of all Malmö children continued beyond compulsory schooling. School enrollment was hence higher than in the rest of Sweden. Malmö was also the first large municipality to extend compulsory schooling to nine years in 1962. Arguably, basic educational infrastructure was well developed and accessible already to the index-generation studied here.

Since the 1920s, loans to help finance higher education were, in principle, available to the tiny fraction of young people qualified to study at universities. In the late 1950s, student loans were also made available for studies at the high school level. The present-day generous grant and loans program for university students was introduced in 1964. Since then, credit constraints are arguably unlikely to play a role for higher education choices.

Appendix 2

How Representative is the Malmö Data?

Table A1 shows the distribution of educational attainments for the third and fourth generations of the GEMS data as compared to the corresponding distribution of the entire Swedish-born population, obtained from the National Education Register of Statistics Sweden, weighted to correspond to the same age distribution across cohorts as the GEMS data.

Table A1 shows that the distribution of educational attainments is remarkably similar for the GEMS data as compared to the entire population for, in particular, the fourth generation. For the third generation, the educational attainments are somewhat lower in the GEMS data. The difference is primarily located at the lower end of the distribution. A plausible reason for this discrepancy is that education in the third generation is measured later in the population sample, leaving more time for individuals to obtain a high school degree or more during the 1990s adult education campaigns.

Table A2 shows earnings at different points in the earnings distribution for the

27. Kockums, a shipbuilding company and mechanical workshop, with 2,300 employees; Skånska Cement, a construction company, with almost 2,000 employees; and Malmö strumpfabrik, a stocking factory, with more than 1,000 employees.

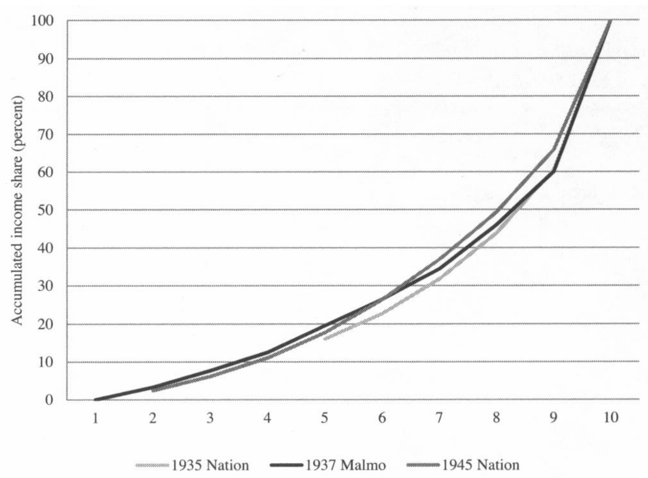

Figure A1

Estimates of Lorenz curves (accumulated income share by decile of the income distribution) for the first generation in GEMS data for the year 1937 compared with those obtained by Bentzel (1952) for Sweden in 1935 and 1945

Source: Own computation based on GEMS data and Bentzel (1952)

Table A1

Distribution of Years of Schooling for the Swedish Population as Compared to the Third and Fourth Generations of GEMS

	Generation 3		Generation 4	
Years of Schooling	Population	GEMS	Population	GEMS
7	6.43	5.10	0.21	0.33
9	12.81	18.98	8.64	9.49
9,5	1.12	1.15	0	0
10	7.18	4.72	2.38	3.84
11	28.05	34.5	10.36	11.68
12	5.24	5.10	25.32	25.78
13	12.51	7.73	18.71	16.68
14	9.32	9.54	8.16	6.75
15	9.48	7.24	17.61	16.79
16	5.51	3.62	7.5	7.62
17	1.38	1.48	0.66	0.66
18	0.12	0.05	0.13	0
20	0.87	0.77	0.32	0.38
All	100	100	100	100

Notes: Education of GEMS individuals is measures in 1985 and 2009 for the third generation and in 2009 for the fourth generation. Educational attainment in the population is measured in 2007 for both the third and the fourth generations. The population averages are restricted to Swedish-born citizens.

Table A2
Distribution of Annual Earnings for the Swedish Population Compared to the Third Generation of GEMS

	Generation 3	
Percentile of the Earnings Distribution	Population	GEMS
1	0	0
5	0	0
10	0.1	0
25	216.1	206.6
50 (median)	313.4	324.0
75	406.5	454.6
90	558.6	669.8
95	701.9	807.9
99	1,138.0	1,261.0

Notes: The table shows annual earnings in SEK thousand at different percentiles in the earnings distribution. The population averages are restricted to Swedish-born citizens.

third generation of the GEMS population and for the population at large. We use register data on annual earnings from 2007 from Statistics Sweden and measured in SEK thousands in 2009 prices. We see that median earnings are slightly higher (3 percent) and that the earnings distribution is somewhat more unequal in the GEMS sample. A plausible explanation for the quite small observed differences is that those included in the GEMS data are more likely to live in the southern parts of Sweden and in metropolitan areas with slightly higher average, but more unequally distributed, earnings. We conclude that although our sample is not a random sample from the Swedish population, Malmö was, and still is, a fairly representative city in Sweden.

Appendix 3

Gender and Intergenerational Transmission

Table A3 investigates how educational transmission varies by gender of ancestor and offspring. The first column of Table A3 shows the bivariate regression of outcomes in each of the last three generations on the educational attainment of the first generation—the great-grandparents—that is, $y_t = a + by_1 + u_t$, where $t = \{2,3,4\}$. Note that the last two sets of rows show the results for academic track of male and female great-grandchildren. Note also that for the first generation, we only have information on male education. In the later generations, we have educational attainment for both men and women. Columns 2 and 3 show results from regressing $y_t = a + by_2 + u_t$, where $t = \{3,4\}$, and so on. The results show that education transmission is invariant to the gender of both offspring and ancestor.

Table A3
Matrix of Estimated Transmission Coefficients Across Generations: Years of Education

	Great-Grandfather (G1)	Grandmother (G2)	Grandfather (G2)	Mother (G3)	Father (G3)
Years of schooling – grandmother (G2)	0.565***				
	(0.076)				
	[0.311]				
	N = 435				
Years of schooling – grandfather (G2)	0.661***				
	(0.118)				
	[0.364]				
	N = 470				
Years of schooling – mother (G3)	0.344***	0.287***	0.273***		
	(0.049)	(0.047)	(0.039)		
	[0.210]	[0.319]	[0.303]		
	N = 831	N = 415	N = 416		
Years of schooling – father (G3)	0.409***	0.322***	0.249***		
	(0.060)	(0.057)	(0.048)		
	[0.250]	[0.357]	[0.277]		
	N = 722	N = 335	N = 387		
Years of schooling – daughter (G4)	0.159***	0.135***	0.117***	0.305***	0.228***
	(0.062)	(0.043)	(0.040)	(0.039)	(0.041)
	[0.135]	[0.208]	[0.181]	[0.425]	[0.318]
	N = 887	N = 461	N = 426	N = 556	N = 331

(continued)

Table A3 (*continued*)

	Great-Grandfather (G1)	Grandmother (G2)	Grandfather (G2)	Mother (G3)	Father (G3)
Years of schooling – son (G4)	0.133**	0.118***	0.146***	0.306***	0.328***
	(0.052)	(0.041)	(0.042)	(0.042)	(0.035)
	[0.113]	[0.183]	[0.226]	[0.426]	[0.458]
	N = 936	N = 483	N = 453	N = 521	N = 886
Academic high school track – daughter (G4)	0.035***	0.022***	0.030***	0.069***	0.055***
	(0.009)	(0.008)	(0.007)	(0.007)	(0.008)
	[0.112]	[0.129]	[0.172]	[0.358]	[0.289]
	N = 1451	N = 713	N = 738	N = 815	N = 636
Academic high school track – son (G4)	0.029***	0.030***	0.028***	0.066***	0.071***
	(0.010)	(0.008)	(0.007)	(0.007)	(0.006)
	[0.093]	[0.176]	[0.160]	[0.343]	[0.368]
	N = 1548	N = 747	N = 801	N = 829	N = 719

Notes: Each reported estimate is from a separate regression of the education of members of one generation on the education of members of an older generation. All regressions control for a quadratic polynomial in birth years of both generations. The reported standard errors (in parentheses) are clustered on families. Standardized estimates are reported in brackets

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