Intergenerational Mobility Across Three Generations in the 19th Century: Evidence from the US Census[*]

Claudia Olivetti

Boston University and NBER

M. Daniele Paserman

Boston University and NBER

Laura Salisbury

York University

February 2014

Abstract

This paper estimates intergenerational elasticities across three generations in the United States in the late 19th and early 20th centuries. We extend the methodology in Olivetti and Paserman (2013) to explore four different channels of intergenerational mobility: fathers-sons-grandsons, fathers-sons-granddaughters, fathers-daughters-grandsons and fathers-daughters-granddaughters.

We document three main findings. First, there is evidence of a strong second-order autoregressive coefficient for the process of intergenerational transmission of income. Second, the socio-economic status of grandsons is influenced more strongly by paternal grandfathers than by maternal grandfathers. Third, maternal grandfathers are more important for granddaughters than for grandsons, while the opposite is true for paternal grandfathers. We propose two alternative theoretical frameworks that can rationalize these findings.

Keywords: Intergenerational Mobility, Multiple Generations, Gender

JEL codes: J62, J12

1 Introduction

The dramatic increase in income inequality over the past 4 decades has led to a renewed interest in how economic status is transmitted across generations. Moreover, the availability of large administrative datasets has pushed the envelope of research on intergenerational mobility, allowing scholars to explore in much more detail the nature of the transmission mechanism across generations (see for example Chetty et al., 2014a and 2014b). One of the most interesting recent developments is the study of the transmission of economic status across multiple generations (Solon 2013, Mare 2011). This extends a large literature (see Solon, 1999 and Black and Devereux, 2011 for extensive surveys) that examined intergenerational mobility across two generations, typically focusing on fathers and sons and assuming that the intergenerational transmission of income follows an AR(1) process. This assumption has been driven primarily by a lack of data linking more than two generations, even though the transmission mechanism may be substantially more complex. [1]

These multigenerational effects have also attracted attention because they have important implications about the persistence of income inequality over time. Most existing estimates place the father-son intergenerational elasticity for the US at between 0.4 and 0.5. If the process of intergenerational income transmission is AR(1), this implies that a given shock to income will fade out relatively quickly: the third order autocorrelation coefficient is between 0.064 and 0.125. A higher order autoregressive process would imply a much slower regression to the mean. In other words, the degree of persistence of socioeconomic status across generations could be a lot higher than what we believe.

A handful of studies have tackled the measurement of multigenerational effects on income transmission using historical data. Ferrie and Long (in progress) measure occupational mobility across three generations by tracing men through federal censuses from 1850 to 1940. They perform record linkages based on first and last name, birth year, and birth place. Clark (2013) and Clark and Cummins (2012) examine intergenerational mobility over the very long term by tracing the performance of men with particular surname characteristics over time. These studies find evidence of significant multigenerational effects; however, the methodolo-

---

[1] Solon (2013) discusses some possible justifications for the inclusion of a second-order term in the lag process: for example, grandparents may make independent human capital investments in grandchildren; alternatively, even if grandparents do not have a direct effect on children's outcomes, the inclusion of multigenerational effects may serve to rectify attenuation bias stemming from the mis-measurement of single generation effects.

gies used impose a major limitation on the type of analysis they are able to do. Both studies use surnames in some capacity to trace families over time; as such, it is impossible for them to say anything about the importance of maternal grandparents, as they cannot be linked to their grandchildren by surname. Moreover, the use of surnames prevents these studies from looking at multigenerational effects on married women's outcomes. As such, they are only able to partially characterize mobility across multiple generations.

In this paper, we attempt to overcome the limitations of existing studies by estimating intergenerational elasticities across three generations for the United States during the late 19th and early 20th centuries, looking at the effects of both maternal and paternal grandparents on both granddaughters and grandsons. We apply and extend the methodology originally developed by Olivetti and Paserman (2013) in order to measure intergenerational elasticities between fathers (G1), children (G2) and grandchildren (G3). The key insight of this approach is that the information about socio-economic status conveyed by *first names* can be used to create a *pseudo-link* between fathers and children. Specifically, our empirical strategy amounts to imputing father's income, which is unobserved, using the average income of fathers of children with a given first name. Extending this idea, one can also impute grandfather's income as a weighted average of the name-specific average income of the fathers' fathers, with weights equal to the fraction of fathers with that name among all the fathers of G3 children with a given first name.[2]

The intuition for why this methodology works can be explained using a simple example. Assume that the only possible names for boys in generation G3 are Adam and Zachary, with high socioeconomic status G2 parents more likely to name their child Adam, with Zachary being more common among low socioeconomic status parents. In a society with a high degree of intergenerational mobility, we would not expect the adult Adams to have much of an advantage on the adult Zacharys. Moreover, in the previous generation (G1) the fathers of men who name their sons Adam should be almost indistinguishable from the fathers of men who name their sons Zachary. Therefore, the correlation in average income of people with a given name, their fathers and their grandfathers will be a good measure of intergenerational mobility.

---

[2]The data only allows us to calculate the intergenerational elasticity in an index of occupational status based on the 1950 income distribution. Somewhat loosely, we will sometimes refer to our estimates as estimates of the intergenerational income elasticity, or simply intergenerational elasticity.

We have claimed to be able to measure the importance of maternal grandparents as well as paternal grandparents. The reason we are able to do this is that our methodology applies equally well to women: just replace Adam and Zachary in the previous example with Abigail and Zelda, and use husband's income as the measure of women's socioeconomic status. Olivetti and Paserman (2013) use this methodology to provide the first estimate of intergenerational mobility between fathers and daughters in the late 19th and early 20th Centuries. In the case of three generations, the methodology will allow us to estimate four different channels of intergenerational transmission of socioeconomic status: fathers-sons-grandsons, fathers-sons-granddaughters, fathers-daughters-grandsons and fathers-daughters-granddaughters. Moreover, we are able to augment a simple AR(2) model of intergenerational income transmission by including the income of *both* paternal and maternal grandparents in the same regression. Thus, our analysis is able to explicitly test the relative importance of paternal and maternal grandparents, which affords it the potential to uncover different mechanisms through which gender differentials in intergenerational mobility may arise.

Using data from the 1850 to 1930 IPUMS US Census 1% samples, we find evidence of a strong second-order autoregressive coefficient for the process of intergenerational transmission of income. That is, even after controlling for the income in generation G2 ("father's income"), the income of generation G1 ("grandfather's income") has a large and positive effect on the income of generation G3 ("grandson's income"). This finding suggests that traditional estimates of intergenerational mobility that assume a first-order autoregressive process for income may substantially understate the true extent of intergenerational persistence in economic status. These findings are in accordance to other recent papers that have been able to exploit modern data that links multiple generations (e.g., Lindahl et al., 2012, and other papers presented at the Panel Study of Income Dynamics "Inequality across Multiple Generations Workshop," September 2012).[3]

The novel contribution of this paper is its ability to study intergenerational elasticities for both genders. Here, we find interesting gender differentials in the strength of the correlation between the three generations. Our results indicate that the transmission of economic status is passed along mostly through gendered lines. That is, paternal grandfathers matter more than maternal grandfathers for the income of grandsons, while the opposite is true for grand-

---

[3]http://psidonline.isr.umich.edu/Publications/Workshops/Multigen2012_Agenda.pdf

daughters. Furthermore, holding the gender of the second generation constant, we find that maternal grandfathers are more important for granddaughters than for grandsons, while the opposite is true for paternal grandfathers.

We propose two alternative theoretical frameworks that can rationalize these findings. The first is a three generation dynastic model in which there is tension between G1's and G2's preferences over G2's (and G3's) consumption. This framework can rationalize our findings if the timing of intergenerational transfers is gender specific; for example, if parents assign dowries to their daughters (when they are still alive) and leave bequests to their sons (upon their death). The second is an intergenerational mobility model in which individuals' desirability in the marriage market is a function of 'market' and 'non-market' traits. This framework can rationalize our findings based on gender asymmetries in the relative importance of market and non-market traits, as well as differences in the degree of inheritability across traits and, potentially, across genders.

The rest of the paper is organized as follows. The next section discusses the methodology as well as the data used for the analysis and some measurement issues. The main results and some robustness checks are presented in Section 3. Finally, Section 4 presents the theoretical frameworks that we use to provide a possible interpretation for our findings.

2 Methodology and Data

We use data from the 1850 to 1930 US Census 1% samples from IPUMS (Ruggles et al., 2010). Even though IPUMS has recently released a set of Linked Representative Samples that link records from 1880 complete count database to each one of the 1850-1930 on percent Census samples, these data do not allow individuals to be linked across more than two generations. Moreover, these data cannot be used to connect married women to their fathers. Therefore, it is necessary to use our methodology to create a data set with information on economic status across three generations. The core idea, as described in the previous section, is to use first names to construct the pseudo-links across cohorts.

Linking generation G2 to generation G3

To link individuals from generations G2 and G3, we follow the same approach used in Olivetti and Paserman (2013). Consider an individual i belonging to G3 who is young at time $t - s$ and adult at time t (in practice, we will look at generations separated by 20 or 30 years). Let y_{it} be individual i's *log earnings* at time t, and y_{it-s} be his father's *log earnings* at time $t - s$. With individually linked data, both y_{it} and y_{it-s} are observed, and the intergenerational elasticity estimate is obtained by regressing y_{it} on y_{it-s}.

Assume instead that we observe G2 and G3 in two separate cross-sections. The first is at time $t - s$, that is, the Census year in which G2 individuals are adults and G3 individuals are children, and the second is at time t, that is, the census year in which G3 individuals are adults. Assume also that it is impossible to link individuals across the two cross-sections. This means that y_{it-s} is unobserved, and it becomes necessary to impute it. Our strategy is to base the imputation on an individual's first name, which is available for both adults and children in each cross-section. In other words, for a G3 adult at time t named j, we replace y_{it-s} with $\tilde{y}'_{jt-s}$, the average log earnings of G2 fathers of children named j, obtained from the time $t - s$ cross section (the "prime" indicates that this average is calculated using a different sample). We have thus created a "generated regressor" by using one sample to create a proxy for an unobserved regressor in a second sample. The income elasticity across generations G2 and G3 can then be estimated by a regression of y_{it} on $\tilde{y}'_{jt-s}$. The regression is run at the individual G3 level, with every G3 adult named j having the same imputed value of his father's income. Olivetti and Paserman (2013) show that if names carry information about economic status, this estimator will be informative of the underlying parameters governing the process of intergenerational mobility.[4] We restrict the sample of G2 fathers to be in the same age range as the sample of G3 adults; this is to facilitate our links to G1, which will be explained in the following subsection.

---

[4]This can be thought of as a "two-sample two-stage least squares" estimator (Inoue and Solon 2010). We rely on this interpretation to derive correct standard errors for our estimates, which take into account the uncertainty embodied in the estimation of the first stage. See Olivetti and Paserman, 2013, for a detailed discussion of the econometric properties of this estimator.

Linking generation G1 to generation G2

Adding a link to generation G1 is slightly more complicated. We would like to impute G1's income to a G3 adult named j as the average income of the grandfathers of children named j in year $t - 2s$. However, two difficulties arise: first, G3 adults in year t would not have been born in year $t - 2s$, so it is impossible to make a "direct" pseudo-link to year $t - 2s$. Second, making "direct" pseudo-links from G1 to G3 would require households to be multigenerational, i.e. containing children and grandfathers residing together, which was not typically the case. Therefore, we proceed as follows. First, we calculate $q'_{j,k}$ as the fraction of fathers (G2) named k of children (G3) named j. This value is taken from Census year $t-s$, in which G2 individuals are adults, and G3 children still live at home with their parents. Second, we calculate $\tilde{y}''_{k,t-2s}$, the average log earnings of G1 fathers of children named k (this average is calculated from Census year $t - 2s$ and we use the "double-prime" to indicate that this average is calculated using yet a different sample). Finally, we calculate $\tilde{y}''_{j,t-2s}$ as:

$$\tilde{y}''_{j,t-s} = \sum_k q'_{j,k} \tilde{y}''_{k,t-2s}$$

In other words, the average log earnings of the grandfathers of G3 adults named j are a weighted average of the name-specific average log earnings of the fathers of G2 fathers, with the weights equal to the fraction of G2 individuals with that name among all the fathers of G3 children named j. For example, suppose that children named Adam in year $t - 20$ have fathers named David, Edward and Fred, in equal proportions. The income assigned to G1 for the group of G3 adults named "Adam" is the weighted average, with weights $\frac{1}{3}$, $\frac{1}{3}$, $\frac{1}{3}$, of the average income at time $t - 2s$ of all fathers of children named David, Edward and Fred, respectively.

One can then merge this cross section to the one linking G3 and G2 by first names, then obtain an estimate of the income elasticity across the three generations by running a regression of $y_{i,t}$ on $\tilde{y}'_{j,t-s}$ and $\tilde{y}''_{j,t-2s}$. Again, this regression is run at the individual G3 level, with all G3 adults with the same first name having identical imputed incomes of G2 and G1.

The description above was presented in terms of the father-son-grandson relationship. It is easy to see, however, that the methodology can be applied to fathers-son-granddaughters,

fathers-daughters-grandsons, and fathers-daughters-granddaughters. Therefore, we will be able to analyze gender differentials in the transmission of economic status across multiple generations.

Data and Measurement Issues

Data with individual names is available from IPUMS for every decadal Census from 1850 to 1930, with the exception of 1890. This means that we can calculate our three-generation measures of intergenerational mobility for two triplets observed at a distance of 20 years from one another (1860-1880-1900, and 1880-1900-1920); and for two triplets of observations observed at a distance of 30 years from one another (1850-1880-1910 and 1870-1900-1930). This gives us a unique long-run perspective on the transmission of economic status across generations.

A challenge that applies to all computations of historical intergenerational elasticities is to obtain appropriate quantitative measures of socioeconomic status. Because income and earnings at the individual level are not available before the 1940 Census, we are constrained to use measures of socioeconomic status that are based on individuals' occupational status. While this contrasts with the current practice among economists, who prefer to use direct measures of income or earnings if available, there is a long tradition in sociology to focus on occupational categories (Erikson and Goldthorpe, 1992). One of the advantages of the IPUMS data set is that it contains a harmonized classification of occupations, and several measures of occupational status that are comparable across years. For our benchmark analysis, we choose the OCCSCORE measure of occupational standing. This variable indicates the median total income (in hundreds of dollars) of persons in each occupation in 1950.

A second challenge arises from our methodology for measuring generation G1 occupational income. As explained above, the income of fathers of generation G2 is computed as a weighted mean of mean incomes by first names. This implies that the distribution of income for G1 is more compressed than that of G2 and G3. This is is apparent from the standard deviation of the average log occupational income of each of the three generations (calculated at the G3 name level). In our sample of G2 and G3 males in 1860-1880-1900, this value is 0.314 for G3, 0.298 for G2, and only 0.091 for G1. As we show below, this inflates the OLS estimate of the G1-G3 intergenerational elasticity relative to the G2-G3 elasticity. Therefore, in most of our

analysis we transform the right hand side variables from log occupational scores to percentile ranks (of the mean income by first name) as a way to get around this problem.

3 Results

3.1 Basic Results

In this section, we present our estimates of intergenerational income elasticities across three generations. Panel A of Table 1 presents these estimates when we use the log occupational income score as our independent variables. The first column shows that the intergenerational elasticity between the 1860 and 1880 cohorts is about 0.29, which is similar in magnitude to the estimate obtained in Olivetti and Paserman (2013), albeit slightly smaller.[5] Column 2 regresses the log occupational scores of G3 males on those of their grandfathers (G1). At approximately 0.6, the coefficient is implausibly large given the size of the estimated G2-G3 intergenerational elasticity. This demonstrates the issue identified earlier: because of the way the variables are constructed, the distribution of G1 earnings is compressed relative to that of G2, which will tend to inflate the coefficient on G1 earnings. Column 3 includes the income of both G1 and G2 males on the right hand side. Both coefficients are statistically significant and quite similar in magnitude. However, we are concerned that this effect may be overstated, given the compression of our measure of G1 income and its apparent effect on the results in column (2).

To overcome this problem, we re-estimate the regressions, but we transform the earnings variables for G1 and G2 from logs to percentile ranks. This should alleviate the problem of excessive compression of the distribution of G1 earnings. The results are presented in panel B of table 1. Column 1 shows the one-generation (G2-G3) estimate of intergenerational mobility. The coefficient in column 1 indicates that going from the bottom to the top percentile of earnings in generation G2 is associated with an increase in log occupational income of about 0.26. Column 2 links G3 to G1, and Column 3 adds the link to G1. As anticipated, the size of the coefficient on G1's earnings rank is substantially reduced. Still, we find that G1's

---

[5]Olivetti and Paserman (2013) estimate the one-generation elasticity in the years 1880-1900 to be 0.34. Our estimate is smaller because we impose the restriction that G2 individuals be between the ages of 20 and 35; this is to facilitate our links to G1. However, a consequence of this restriction is that the number observations in G2 declines, leading to increased attenuation bias in the estimated one-generation elasticity.

earnings rank has a significant positive effect on the log earnings of G3, even after controlling for the earnings rank of G2. The statistically significant coefficient on G1 income implies that the intergenerational income transmission process is better characterized as an AR(2), and ignoring the second order autoregressive term will lead to overstating the extent of long-run mobility across generations.

The IPUMS Linked Representative Samples provide an opportunity to test this methodology. These data contain true links between fathers and sons, which allow us to compare results obtained from our pseudo panels to results obtained using actual father-son pairs. Using the sample that links individuals from the 1880 to 1900 censuses, we define G3 income as the income of the adult in 1900, and G2 income as the income of this person's father in 1880; this is a true link. To obtain G1 income, we create a pseudo link: because we observe the name of the individual's father in 1880, we can calculate the average income of fathers of boys with this name in 1860. This allows us to create a panel in which all links are "direct," so we do not face issues related to the compression of the earnings distribution of certain generations relative to others.

Table 2 replicates table 1 using the linked IPUMS data. The top panel contains regressions using log occupational income as explanatory variables; in the bottom panel, we use percentile ranks on the right hand side. Columns (2) an (3) of the top panel of table 2 confirm our concerns about the coefficients in the top panel of table 1. The coefficients on G1 in this table are significantly smaller than the corresponding coefficients in table 1.[6] It is encouraging that the coefficients in the bottom panel of table 2 are similar to those in the top panel of the table, and that the coefficients on G1 in the bottom panel of table 1 are similar to the coefficients on G1 in both panels of table 2. This suggests that our percentile rank regressions offer a more accurate picture of the true G1-G3 intergenerational elasticity. We will continue to use this method for the duration of the paper.

3.2 Gender Differentials

Table 3 presents regressions of G3 earnings on the percentile rank of earnings of G1 and G2, using all possible gender combinations and both decade triplets in which the distance between

---

[6]Notice that the coefficients on G2 are much larger in the top panel of table 2 than they are in table 1. This is due to differences in the extent of measurement error in these two tables. In table 2, the links between G3 and G2 are actual links as opposed to pseudo links, which reduces attenuation bias in the estimates.

generations is 20 years (1860-1880-1900; 1880-1900-1920). Notice that the coefficient on G1 is positive and significant in all but one case. This offers further support for the existence of multigenerational effects. There also appears to be a slight upward time trend: in all but one gender pairing (G2 male and G3 female), the coefficient on G1 is higher in the latter time period. As in Olivetti and Paserman (2013), we also find an upward trend in the G2 coefficient: one-generation mobility in the US declines between the late part of the 19th and the early part of the 20th Century.

This table already illustrates some gender differences in the G1-G3 intergenerational elasticity by gender. First, consider how the G1-G3 coefficient is affected by the gender of G2. For G3 males, the G1-G3 intergenerational elasticity is always greater when G2 is male. To see this, compare columns (1) and (2) in both panels. This suggests that grandsons are more heavily influenced by paternal grandfathers than maternal grandfathers. For G3 females, on the other hand, there is no obvious pattern; this can be seen from a comparison between columns (3) and (4).

The intergenerational elasticity also appears to be affected by the gender of G3. When G2 is female, the G1-G3 intergenerational elasticity is clearly greater for G3 females, as is apparent from columns (2) and (4). This means that maternal grandfathers have a greater influence on their granddaughters than their grandsons. On the other hand, a comparison between columns (1) and (3) suggests that there is no such difference for paternal grandfathers: there is no systematic difference in the coefficient of G1 by the gender of G2.

Table 4 repeats the analysis in Table 3 using decade triplets separated by 30-year intervals (1850-1880-1910; 1870-1900-1930). These coefficients do not systematically differ in magnitude from those in Table 2. This table provides support for the existence of an upward time trend: in three out of four cases, the coefficient on G1 earnings is higher in the latter period, and in all four cases the coefficient on G2 is higher. The two gender differences seen in Table 3 are borne out in Table 4: grandsons inherit more from paternal than maternal grandfathers (columns 1 and 2), and maternal grandfathers pass on more to granddaughters than grandsons (columns 2 and 4). We explore these gender differences further in the subsequent sections.

Our methodology allows us to go a step further in illustrating the gender differences in the G1-G3 intergenerational elasticity. Specifically, we are able to regress G3 earnings on the earnings of maternal and paternal grandfathers together. To see how this can be accomplished,

11

consider the following example. Suppose there is one G3 child named Adam in 1880, and his parents (both between the ages of 20 and 35) are named Bill and Barbara. The (G2) earnings of both Bill and Barbara will be defined as Bill's earnings, as we are defining a woman's earnings as those of her husband. Paternal G1 earnings will be the average earnings of fathers of children named Bill in 1860; similarly, maternal G1 earnings will be the average earnings of fathers of children named Barbara in 1860. These values can both be included in a regression of Adam's (G3) earnings in 1900 on the earnings of G2 and G1. The advantage is that we can directly test whether or not paternal grandparents have a greater effect on grandchildren's earnings than maternal grandparents, which is what our results so far suggest (at least for G3 males).

These results are presented in Table 5. The regressions are run separately for G3 males and females, and the coefficients are reported side by side. The bottom row of both panels contains the p-value from a test of the equality of the coefficients on paternal and maternal G1. For G3 males, the coefficient on paternal G1 is quite significantly higher than the coefficient on maternal G1 in three out of four cases; in the fourth case, they are statistically indistinguishable from each other. For G3 females, the coefficient on maternal G1 is higher than the coefficient on paternal G1 in three out of four cases, but this difference is only significant at the five percent level in one case.

Looking across equations, we see that the coefficient on maternal G1 tends to be higher for G3 females than for G3 males, and this is also significant in three out of four cases. The opposite is true of the coefficient on paternal G1: this tends to be higher for G3 males. These results are consistent with our other findings on gender differences in the transmission of income across three generations.

3.3 Robustness

Having reported our basic set of results, we go on to test the sensitivity of these results to certain features of our sample design and our method of measuring earnings. Our findings make use of a ranking of occupations based on the 1950 occupational wage distribution. If this wage distribution in 1950 differs from the wage distribution during the periods we focus on, this may affect our results. Most importantly, our results are likely to be sensitive to the placement of farmers in the occupational wage distribution, as farmers comprise a very

12

large fraction of the occupations in our sample. To test the sensitivity of our results to the occupational ranking, we use an occupational income distribution from 1900, and we impute a wage for farmers using data from the 1900 Census of Agriculture. The 1900 occupational wage distribution is obtained from the tabulations in Preston and Haines (1991), based on the 1901 Cost of Living Survey. These tabulations are based on the 1901 Cost of Living Survey, which was designed to investigate the cost of living of families in industrial locales in the United States.[7] Preston and Haines explicitly refrained from imputing an average income for generic farm owners. To fill this gap, we impute farmer's income using data from the 1900 Census of Agriculture and a method based on Abramitzky et al. (2012).

To further test that our results are not sensitive to our occupational wage measure, we construct a measure based on personal property reported in 1860 and 1870. This is advantageous because it corresponds to the earlier periods in our analysis. We calculate mean personal property of household heads by occupation, pooling data from 1860 and 1870 and adjusting for price differences between these two decades. One issue is that farmers' personal property consists largely of equipment or resources used in farming; as such, it does not make sense to think about this property as a measure of labour income. In fact, including this property will likely overstate the status of farmers considerably. We adjust farmers' personal property downward by the average value of farm equipment and livestock in 1860 and 1870, using national average values from the census of agriculture (Haines and ICPSR 2010).

We report results using the 1900 wage distribution and the 1860-1870 occupational wealth distribution in Table 6. We estimate the coefficient on maternal and paternal grandparents simultaneously, as we did in table 5. When we use the 1900 wage distribution, the magnitude of the G1-G3 elasticity is quite comparable to that obtained using the 1950 occupational wage distribution, and in almost all cases statistically significant at conventional confidence levels. When we use the 1860-1870 wealth distribution, the coefficients are typically larger. However, in both cases, the gender differences in the G1-G3 elasticities remain. Altogether, we conclude that our results are not overly sensitive to the exact measurement of income. We also tested the sensitivity of our findings to including controls for age, immigrant status, and literacy (results not reported). These controls do not have a dramatic effect on the coefficients on G1

---

[7]One limitation of this measure is that the survey collected data for the "typical" urban family, meaning that, by construction, the resulting income distribution is more compressed than what one would obtain in a representative sample.

earnings, and they do not alter the underlying patterns we find.

Our main finding pertains to gender differences in the process of income transmission across three generations. However, we are concerned that comparisons by gender may be sensitive to the way our samples are constructed. For example, we measure a woman's socioeconomic status by the earnings of her husband. This means that all women in our sample are married, whereas men need not be married to be included. Then, we may be measuring differences in intergenerational income transmission by marital status rather than gender. Furthermore, we do not place restrictions on the age of these husbands in our baseline specification; therefore, our results may reflect the fact that we are measuring income at different points in the life cycle for women and men.

To ensure that our results are not being driven by these details of our sample construction, we redo the analysis imposing different restrictions on G2 and G3. The additional restriction we impose on G2 is that individuals in the sample be married to a spouse in the same age range as the individual (20-35 or 30-45, depending on the sample years). We impose two additional restrictions on G3. First, we restrict individuals to be married; second, we restrict individuals to be married to a spouse in his or her age range. We calculate the G1-G3 intergenerational elasticity for each of 6 combinations of these sample restrictions (including the baseline sample restrictions). The results, using the 1860-1880-1900 sample, are reported in Appendix Table 1.

To summarize the results of the above robustness analysis, we compile all G1-G3 intergenerational elasticities estimated under different sample restrictions in each decade triplet. There are 96 such estimates.[8] We regress these on indicators for the decade in which G2's earnings are measured (1880 or 1900), the interval that separates generations (20 or 30 years), the gender of G2, the gender of G3, and categorical variables indicating which sample restrictions are imposed. Standard errors are clustered at the specification level. We report these results in Appendix table 2. In column (1) we pool all specifications, and in the remaining columns we separate them by gender. Column (2) contains only G3 males, and column (2) contains only G3 females; similarly, column (4) contains only G2 males, and column (5) contains only G2 females.

---

[8]Four possible combinations of G2 and G3 gender; two time intervals; two time periods; two possible sample restrictions on G2; and three possible sample restrictions on G3: $4 \times 2 \times 2 \times 2 \times 3 = 96$.

This exercise supports the existence of an upward time trend in the G1-G3 intergenerational elasticity, and it suggests that this elasticity declines as the interval at which cohorts are constructed increases. While there is no overall tendency for the coefficient to be higher when G2 is male, the picture changes dramatically when we segregate G3 by gender. For G3 males, the effect is clearly stronger when G2 is male. For G3 females, there is no clear difference; if anything, the effect smaller is when G2 is male, but this difference is not statistically significant. Again, there is no significant difference in the G1-G3 intergenerational elasticity by gender of G3 overall, but this masks significant differences when we separate by gender of G2. When G2 is female, the effect is much stronger for G3 females; the opposite is true of G2 males.

3.4 Regional Differences

To provide further insight into the gender differences we find in the G1-G3 intergenerational elasticity, we estimate versions of table 5 that exclude different regions. These results are presented in table 7. In panel A, we estimate the effect of both paternal and maternal G1's occupational rank on G3's occupational rank for all decade triplets, excluding observations in the northeast from the analysis. By and the large, the overarching patterns we found for the entire U.S. persist when we exclude the northeast: G1 paternal has a greater effect that G1 maternal for G3 males in three out of four cases, and G1 maternal has a greater effect on G3 females than G3 males in all cases. However, G1 paternal only has a greater effect on G3 males than G3 females in two out of four cases. Still, the broad picture looks very similar to the entire U.S. when we include the northeast. In panel B, we exclude the midwest; in general, the same gender based patterns can be seen here as well.

In panel C, we exclude observations in the south. In contrast to the northeast and the midwest, excluding the south has a dramatic effect on our results. The effect of G1 paternal is greater than the effect of G1 maternal for G3 males in three out of four cases. However, this is the only nation-wide pattern that holds in a majority of cases when we exclude the south. This suggests that the south is an important driver of the patterns we are finding. In the next section, we will propose a model for interpreting these results.

4 Interpretation

The empirical analysis in the previous sections has uncovered a number of interesting stylized facts on the intergenerational correlations between grandchildren and their paternal and maternal grandfathers. We use the notation $\rho_{g,PAT}$ and $\rho_{g,MAT}$ to denote correlations between grandchildren of gender g with their paternal and maternal grandfathers, respectively. The results of the previous sections can be summarized as follows: a) the correlation of male grandsons with their paternal grandfathers is stronger than the correlation with their maternal grandfathers ($\rho_{M,PAT} > \rho_{M,MAT}$); b) the correlation between female granddaughters with their maternal grandfathers is stronger than that with their paternal grandfathers ($\rho_{F,MAT} > \rho_{F,PAT}$); c) the correlation between paternal grandfathers and grandsons is stronger than the correlation between paternal grandfathers and granddaughters ($\rho_{M,PAT} > \rho_{F,PAT}$); d) The correlation between maternal grandfathers and granddaughters is stronger than the correlation between maternal grandfathers and grandsons ($\rho_{F,MAT} > \rho_{M,MAT}$). We now discuss two alternative mechanisms that can rationalize our findings.

4.1 Intergenerational Time Inconsistency

To explain why the effect of paternal grandfathers may differ from that of maternal grandfathers, we present a simple three-generation dynastic model of consumption and human capital investment. The key ingredient of the model is that there is a tension between the desired allocation of consumption across the three generations across the decision-makers in generations 1 and 2. This tension derives from the fact that each generation discounts heavily the utility of future generations relative to its own utility, but the discount factor between any two future generations is relatively low. In other words, each generation is characterized by quasi-hyperbolic, or $\beta - \delta$ preferences.[9] The investment in the third generation's human capital depends on whether the second generation is able to reoptimize over the allocation of resources between G2 and G3, or whether it must follow the allocation chosen by G1. We conjecture that, because of the the timing of transfers across generations and the marriage in-

---

[9]Quasi-hyperbolic preferences have been made popular in recent years to model the intra-personal self-control problems in consumption and savings decisions and other contexts (Laibson, 1997; O'Donoghue and Rabin, 1999; DellaVigna and Paserman, 2005). However, one of the first applications of $\beta - \delta$ preferences (Phelps and Pollak, 1968) was to an intergenerational growth model very much like the one considered here.

stitutions prevailing in the 19$^{\text{th}}$ Century [10], second generation daughters (and their husbands) may have been more likely to reoptimize, thus inducing the lower elasticity between first and third generation's income when the second generation is female.

Formally, we consider a three-generation dynasty. Each generation derives utility from its own consumption and from that of the following generations. Therefore:

$$U_1 \left(c_1, c_2, c_3 \right) = \ln \left(c_1 \right) + \beta \delta \ln \left(c_2 \right) + \beta \delta^2 \ln c_3$$

$$U_2 \left(c_1, c_2 \right) = \ln \left(c_2 \right) + \beta \delta \ln \left(c_3 \right)$$

$$U_3 \left(c_3 \right) = \ln \left(c_3 \right)$$

We assume throughout that $\beta < 1$, reflecting the fact that each generation puts more weight on its own utility relative to future generations' utility; and $\delta < 1$, reflecting the fact that the weight placed on more distant generations' utility also declines. Notice that for G1, the discount factor between its own utility and that of G2 is $\beta \delta$, while the discount factor between G2 and G3's utility is only δ. This captures the fact that the discount rate between the present and any period in the future is higher than the discount rate between any two periods in the distant future.

Each generation can allocate its income Y_t between its own consumption c_t and investment in the following generation's human capital, I_{t+1}. Generation $t + 1$'s income is a function of generation t's investment:

$$Y_{t+1} = R I_{t+1}.$$

To solve for the optimal allocation of resources across generations, we consider two alternative possibilities. In the first case, G1 decides on how to allocate resources for all three generations. In the second case, G2 can reoptimize and decide on the allocation of resources from that point onwards. G1's decision takes into account G2's decision, and decides how

---

[10]In America and England, the doctrine of *coverture* would imply that a woman, and her assets, would become the property of their husbands upon marriage. See Geddes and Lueck, 2002, for a property right analysis of coverture and its demise in the United States.

much to consume and how much to invest in the next generation as a best response to G2's actions. In the language of the quasi-hyperbolic discounting literature, the first case corresponds to that of an agent who can perfectly commit to the full sequence of decisions made in period 1 (call this the *commitment* regime), while the second case corresponds to that of a sophisticated agent (the *sophistication* regime).

It is easy to show that the income of the second generation is the same under both regimes, while the income of the third generation is lower in the sophistication regime than in the commitment regime. The intuition for the second result is straightforward. If G1 can commit to a given consumption path for all three generations, it will allocate resources between G2 and G3 in a relatively egalitarian way: from its perspective, G3's utility is discounted only by a factor δ relative to G2's utility. On the other hand, if G2 can reoptimize given its allocation, it will put more weight on its own consumption, as the discount factor that it applies between its own utility and G3's utility is $\beta\delta$.[11]

How do these results relate to our findings on how the strength of the G1-G3 intergenerational elasticity depends on the gender of the middle generation? We argue that the allocation of resources will resemble that in the commitment regime if G2 is male, but it will be more like that of the sophisticated agent if G2 is female. This difference arises because of a combination of marriage institutions (and specifically the allocation of property rights within the marriage), postmarital location norms, and the differential timing of transfers to sons and daughters.

First, we note that the United States in the 19th Century was very much a *virilocal* society, where married daughters leave their parental nest, while married sons do not. A quick examination of the 1880 and 1900 IPUMS samples reveals a tendency for young married couples to reside with husbands' rather than wives' parents. During the period of focus of this study, only 10-12 percent of married couples under 35 resided in the same household as a parent; however, that parent was significantly more likely to belong to the husband. This is especially true of agricultural families: young couples residing with a parent were twice as likely to be living with the husband's parents rather than with the wife's parents. This may also mask a tendency for families to reside in the same locality as the husband's parents, even if they do not reside in the same household. Families' residential locations by themselves were likely

---

[11]The result that the second generation's income is identical under both allocation rules is less interesting, and depends on the specific functional form of the utility function (logarithmic utility).

to affect the degree of control of the first generation over the allocation of resources by the second generation. Paternal grandparents, were likely better able to monitor the decisions of their sons who lived in close vicinity, and may have been able to transfer resources directly to their grandchildren.

The residential location of married children may also affect the timing of transfers from parents. For example, Botticini and Siow (2003) argue that in virilocal societies, altruistic parents will leave dowries to their daughters and bequests to their sons to mitigate a free-rider problem. Other papers focus on the role of marital arrangements, with males remaining close to their parents' households and specializing in farm production and women moving to new households, for consumption smoothing and agency problems (see for example, Rosenzweig and Stark, 1989, based on data on rural India; and Fafchamps and Quisumbing, 2005a and 2005b, on rural Ethiopia). Even though formal dowries were relatively uncommon in North America in the 19th Century, [12]it is possible that, because of these living arrangements, transfers from parents to daughters were more likely to occur at marriage than were transfers from parents to sons.

The timing of intergenerational transfers for daughters, coupled with the legal environment in place during the period of analysis, may affect the ability of the second generation to decide on the allocation of consumption between itself and the third generation. Assume that, as discussed above, G2 daughters receive transfers from their parents upon marriage. In the 19th Century, women completely relinquished control of their assets to their husbands. Under the doctrine of coverture, a husband owned any wages earned by his wife and any property she brought to the marriage (Geddes and Lueck, 2002). States began to lift some of these restrictions in the second half of the Century, but it was not until 1920 that coverture had effectively disappeared.

Therefore, it seems reasonable that, in the presence of a daughter, the G1 patriarch would have had little say over the allocation of resources between G2 and G3. On the other hand, G2 sons were more likely to receive a bequest, only upon G1's death. The fact that G1 could withhold the transfer of resources to his male offspring implies that it was also easier for G1 to monitor the allocation of resources between G2 and G3, and therefore guarantee that the

---

[12]Botticini and Siow (2003) document that in late 18th Century Connecticut, between 46 and 67 percent of married daughters were assigned inter vivos transfers from their family of origin, likely at the time of their marriage. However, by 1820's, only 40 percent received such transfers.

investment in the grandchild's human capital would be sufficiently high.

4.2 Multi-trait Matching and Inheritance

The predictions of the previous model are the same for both grandsons and granddaughters and suggest that paternal grandfathers should matter more than maternal grandfathers. By contrast, the empirical evidence points to a larger effect of the paternal grandfather only for grandsons, while in fact for granddaughters it appears that the maternal grandfather matters more. In the following, we present an alternative model that can rationalize the pattern of relative importance of maternal and paternal grandfathers observed in the data. The model is an adaptation of Chen et al. (2013)'s model of intergenerational mobility and multi-trait matching, which allows for multiple generations.

The basic premise of the model is that individuals' attractiveness in the marriage market is a function of 'market' and 'non-market' traits. Market traits directly affect an individual's earning potential. They can include elements such as cognitive skills or education. The degree of persistence in the transmission of the market trait may depend on the parents' willingness and ability to invest in the children's human capital, and on the institutional set-up (for example, credit constraints, public spending in education, etc). Non-market traits do not directly affect earnings potential. They can include attractiveness, height, kindness, emotional stability – all things that potentially have little impact on market productivity but are valued in the marriage market.

The observed gender differences in social mobility can be rationalized based on asymmetries between market and non-market traits. The first is an asymmetry in the relative importance of these two traits across genders. In particular, market traits are more important in determining the desirability of men in the marriage market, while non-market traits are more important for women. This difference can be explained based on biological differences in reproductive roles and on the persistence of gender roles within households. Even today, evidence based on on-line dating and speed-dating shows that men and women value different attributes in prospective partners (see, for example, Fisman et al., 2006). The second is a potential difference in the degree of inheritability of market and non-market traits. For example, market traits (e.g., education) may be more persistent across generations because they are more amenable to parental investments than non-market traits (e.g., physical appearance or reproductive

ability).[13] In addition, there could be gender differences in the degree of inheritability of the market trait caused by institutions that might make parental investment in the market trait more beneficial for children of one gender than of the other. This limited set of assumptions is able to deliver a rich set of predictions on the pattern of correlations between grandchildren (of both sexes) and their paternal and maternal grandfathers.

Basic setup and marriage market equilibrium

To formalize matters, we assume that the economy is populated by an equal number of men and women, each characterized by two traits, x and y. Let y be the 'market' trait, which directly affects an individual's earning potential (e.g., cognitive skills, or education); and x be the 'non-market' trait, which is not directly productive in the labor market, but is valued in the marriage market (e.g., physical attractiveness, health, kindness, etc.).

In the marriage market, every individual is characterized by a unique index of attractiveness, which depends on the individual's x and y traits: $h_i^G(x_i, y_i) = x_i + \phi^G y_i$, $G = F, M$. The matching equilibrium in the marriage market features perfect assortative mating: the highest ranking man is matched with the highest ranking woman, the second highest man with the second highest woman, and so on.

Our first critical assumption is that the attractiveness function $h^G(\cdot)$ differs by gender. Specifically, the non-market trait x has higher weight in determining women's desirability, $\phi^F < 1$, while the market trait y is more important for men, $\phi^M > 1$. To further simplify matters, we assume that each trait can take only one of two levels: $x \in \{\underline{x}, \ \overline{x}\}$ and $y = \{\underline{y}, \ \overline{y}\}$.

Therefore, the equilibrium in the marriage market takes on a particularly simple form,

---

[13]If the extent to which parents can invest in their children's non-market traits is more limited, the degree of persistence in the transmission of the non-market trait will also be more limited. Mailath and Postlewaite, 2006, argue that these 'unproductive' traits can be thought of as 'social assets' in equilibrium. For example, height might not have an intrinsic value but may become valuable if all agents in the economy believe that height is a desirable quality (this is a similar argument to that used for the emergence of fiat money).

summarized by the table below:

Ranking of Couples	Females	Males
1	$(\overline{x}, \overline{y})$	$(\overline{x}, \overline{y})$
2	$(\overline{x}, \underline{y})$	$(\underline{x}, \overline{y})$
3	$(\underline{x}, \overline{y})$	$(\overline{x}, \underline{y})$
4	$(\underline{x}, \underline{y})$	$(\underline{x}, \underline{y})$

There are four categories of individuals: men and women endowed with high levels of both traits (i.e., the highest ranked individuals) are paired with each other, as do men and women endowed with low levels of both traits (the lowest ranked individuals). However, in the middle two categories, there is some mixing: men with high levels of the market trait ($\overline{y}$) and low levels of the non-market trait ($\underline{x}$) are matched with women with low levels of the market trait and high levels of the non-market trait ($\underline{y}$ and $\overline{x}$), while men with ($\underline{y}$, $\overline{x}$) are matched with women with ($\overline{y}$, $\underline{x}$).

Transmission of traits across generations

To understand the implications of this matching model for intergenerational mobility, we must consider how the two traits are transmitted across generations. First, we assume that every couple has exactly one son and one daughter, so that in each generation there will be an equilibrium in the marriage market where each individual is matched to one of the opposite sex. Next, we assume that for both traits x and y, a child can either be endowed with the same level of the trait as his/her parent, or he/she can "switch" – i.e., if the parent is endowed with a high level of the trait, the child will be endowed with a low level, and vice versa.

Let π_x^g and π_y^g be the probabilities that, respectively, traits x and y "switch" for a child of gender g ($g = M, F$). In the most general case, these switching probabilities are allowed to differ both by trait and by gender, reflecting both institutional and biological factors. We capture the fact that traits are relatively persistent across generations by constraining the "switching" probabilities to be weakly smaller than $1/2$. Clearly, lower values of the switching probabilities imply that a trait is highly persistent across generations.

Our next key assumption is that the transmission of traits x, y is gender-segregated: specif-

ically, we assume that the father passes on his traits to the son , and the mother passes on her traits to the daughter. While this assumption is clearly extreme (in reality it is likely that children inherit traits from both their parents), we view it as a convenient simplification, which captures the fact that children will be more inclined to view the parent of their same sex as a role model to imitate. Finally, we assume that the transmission of the x and y traits are independent of each other and across genders.

Putting everything together, we can derive a two-generation transition probability matrix where the (j, k) element is the probability of generation $t + 1$ being in rank k conditional on generation t being in rank j. Note that because of the nature of the matching equilibrium, the transition matrices are not identical for men and women. For example, a man born to the highest rank will move to the second highest rank only if the x trait switches and the y trait does not switch, an event that occurs with probability $\pi_y^M \left(1 - \pi_x^M \right)$. On the other hand, a woman in the highest rank will move to the second highest rank only if trait x stays the same but trait y switches, an event that occurs with probability $(1 - \pi_x^F)\pi_y^F$. The resulting transition matrices, which we denote with Π_M and Π_F, can be found in the appendix.

Three generation transition matrices and intergenerational correlations.

Consider now the three-generation transition probability matrices, whose (j, k) element is equal to the probability that a grandchild belong to rank k, conditional on the grandfather belonging to rank j. There are four such matrices, depending on the gender of the grandchild and the gender of the middle generation.

It is easy to show that the three generation transition matrices are obtained from the product of the two-generation matrices, Π_M and Π_F. Specifically:

$$
\begin{aligned}
\Omega_{M,PAT} &= \Pi_M \Pi_M \\
\Omega_{M,MAT} &= \Pi_F \Pi_M \\
\Omega_{F,PAT} &= \Pi_M \Pi_F \\
\Omega_{F,MAT} &= \Pi_F \Pi_F.
\end{aligned}
$$

The corresponding three-generation rank correlations, $\rho_{g,G}$, for $g = \{M, F\}$ and $G =$

$\{MAT, PAT\}$, can be written as

$$\rho_{g,G} = \frac{\frac{1}{4}r'\Omega_{g,G}r - E(R)^2}{V(R)},$$

where $r = \begin{pmatrix} 1 & 2 & 3 & 4 \end{pmatrix}'$ and R is the random variable denoting an individual's rank, and has a discrete uniform distribution between 1 and 4.

Explicit formulas for these intergenerational correlations are presented in the appendix. Here we discuss the differences, $(\rho_{M,PAT} - \rho_{M,MAT})$ and $(\rho_{F,MAT} - \rho_{F,PAT})$, that are relevant for the interpretation of our findings. Specifically, we are interested in finding conditions such that both differences are positive, i.e., paternal grandfathers matter more for grandsons, but maternal grandfathers matter more for granddaughters. Sufficient conditions for both inequalities to hold are the following:

$$\pi_y^M < \pi_x^F$$
$$\pi_y^F < \pi_x^M$$
$$\frac{1}{4}\frac{(1 - 2\pi_x^M)}{(1 - 2\pi_y^M)} < \frac{(\pi_x^F - \pi_y^M)}{(\pi_x^M - \pi_y^F)} < \frac{1}{4}\frac{(1 - 2\pi_y^F)}{(1 - 2\pi_x^F)}.$$

The first inequality states that the switching probability of the dominant trait for men (π_y^M) must be smaller than the switching probability of the dominant trait for women (π_x^F). This amounts to saying that the transmission of market skills for men is more persistent than the transmission of non-market skills for women. The second inequality states that the transmission of the less important trait is also more persistent for men than for women. The third inequality bounds the ratio of $(\pi_x^F - \pi_y^M)$ to $(\pi_x^M - \pi_y^F)$, so that the empirical patterns in the data are respected.

To gain some intuition on the meaning of these conditions, it is instructive to analyze the special case in which $\pi_y^M = \pi_y^F \equiv \pi_y$ and $\pi_x^M = \pi_x^F \equiv \pi_x$. In this case, the conditions boil down to an even simpler form:

$$\pi_x > \frac{3}{8}$$
$$\pi_y < -\frac{3}{2} + 4\pi_x.$$

24

In short the conditions tell us that the switching probability for the x trait (non-market skills) must be sufficiently high, while the switching probability for the y trait (market skills) must be relatively low.

Consider what these values imply for the descendants of a generation 1 grandfather who has high levels of both the x and y traits, and therefore belongs to the highest rank. The low value of π_y implies that G2 sons are likely to maintain the high value of the market trait, and therefore are likely to remain in one of the top two ranks. Since the traits are passed along the male line, the G3 male is also likely to stay in one of the top two ranks. Hence, the correlation between grandson and paternal grandfather is likely to be high. Compare this to the outcome of the maternal grandson (the son of a G2 female). The G2 daughter inherits her traits from her mother, who, because of perfect assortative mating, is also endowed with high levels of both x and y. The relatively high value of π_x implies that the G2 daughter has a relatively high probability of ending up in the third rank, characterized by low levels of non-market skills ($\underline{x}$) and high levels of market skills ($\overline{y}$), and will therefore marry an $(\overline{x}, \underline{y})$husband. But then, the male grandson will likely inherit the low levels of the y trait from his father, and remain in one of the two lowest ranks. Within two generations, the maternal grandson will have experienced considerable downward mobility in economic status.

Let us now turn to the outcomes of the granddaughters. Along the female line, the G3 granddaughter will inherit the traits of her mother, who, as described above, is likely to be in either the first or the third rank, and therefore endowed with a high level of y. Because of the high value of π_x and the low value of π_y, the G3 daughter is also likely to remain in either the first or the third rank. Take instead the paternal granddaughter: the G2 son is likely to maintain the high level of y and therefore remain in either the first or second rank. If the latter, the son will be matched to an $(\overline{x}, \underline{y})$ wife. This implies that the G3 granddaughter, inheriting the traits of her mother, is also likely to have a low level of y, and therefore will likely be in either the second or fourth rank. The end result is that the paternal granddaughter is more likely to be more removed from her $(\overline{x}, \overline{y})$ grandfather than the maternal granddaughter.

Similar arguments apply to grandfathers who start out in one of the other categories. In short, we have shown that with a relatively parsimonious set of assumptions, our simple model is able to deliver a rich set of predictions that matches the pattern of intergenerational correlations that is observed in the data.

5   Conclusion

In this paper, we have estimated intergenerational elasticities across three generations for the US spanning the late 19th and early 20th Century. We find that the intergenerational income process exhibits a strong second-order autoregressive coefficient. We also find that the grandfather-grandchild intergenerational elasticity is larger when the middle generation is male, and we rationalize these findings using a simple three-generation dynastic model where there is a tension between G1's and G2's preferences over G2's consumption, and the timing of transfers is gender specific. These results can have important implications for our understanding of the persistence of socioeconomic status over the long run.

References

[1] Abramitzky, Ran, Leah Platt Boustan and Katherine Eriksson (2012). "Europe's Tired, Poor, Huddled Masses: Self-Selection and Economic Outcomes in the Age of Mass Migration." *American Economic Review,* 102(5), pp. 1832-1856.

[2] Black, Sandra E. and Paul J. Devereux (2011). "Recent Developments in Intergenerational Mobility," in (O. Ashenfelter and D. Card, eds.), *Handbook of Labor Economics*, Volume 4B, pp. 1487-1541, Amsterdam: North-Holland.

[3] Botticini, Maristella and Aloysius Siow (2003). "Why Dowries?" *American Economic Review*, 93(4), pp. 1385-1398.

[4] Chen, Natalie, Conconi, Paola and Carlo Perroni (2013). "Multi-Trait Matching and Gender Differentials in Intergenerational Mobility." *Economic Letters*, 102(2), pp. 292-296.

[5] Chetty, Raj, Hendren, Nathaniel, Kline, Patrick and Emmanuel Saez (2014a). "Where is the Land of Opportunity? The Geography of Intergenerational Mobility in the United States." National Bureau of Economic Research Working Paper 19843.

[6] Chetty, Raj, Hendren, Nathaniel, Kline, Patrick, Saez, Emmanuel and Nicholas Turner (2014b). "Is the United States Still a Land of Opportunity? Recent Trends in Intergenerational Mobility." National Bureau of Economic Research Working Paper 19844.

[7] Della Vigna, Stefano and M. Daniele Paserman (2005). "Job Search and Impatience." *Journal of Labor Economics*, 23(3), pp. 527-588.

[8] Erikson, Robert and John H. Goldthorpe (1992). *The Constant Flux: A Study of Class Mobility in Industrial Societies.* Oxford: Clarendon Press.

[9] Fafchamps, Marcel and Agnes Quisumbing (2005a). "Assets at Marriage in Rural Ethiopia." *Journal of Development Economics*, 77(1), pp. 1-25.

[10] Fafchamps, Marcel and Agnes Quisumbing (2005b). "Marriage, Bequest, and Assortative Matching in Rural Ethiopia." *Economic Development and Cultural Change*, 53(2), pp. 347-380.

[11] Fisman, Raymond; Sheena S. Iyengar; Emir Kamenica and Itamar Simonson. (2006) "Gender Differences in Mate Selection: Evidence from a Speed Dating Experiment." *Quarterly Journal of Economics*, 121(2), pp. 673-697.

[12] Inoue, Atsushi and Gary Solon (2010). "Two-sample Instrumental Variables Estimators." *Review of Economics and Statistics*, 92(3), pp. 557-561.

[13] Laibson, David I. (1997). "Golden Eggs and Hyperbolic Discounting." *Quarterly Journal of Economics*, 112(2), pp. 443-477.

[14] Lindahl, Mikael; Marten Pålme; Sophia Sandgren Massih and Anna Sjögren. (2012). "The Intergenerational Persistence of Human Capital: An Empirical Analysis of Four Generations." IZA Discussion Paper No. 6463.

[15] Mailath, George J. and Andrew Postlewaite (1996). "Social Assets." *International Economic Review*, 47(4), pp. 1057-1091.

[16] O'Donoghue, Ted and Matthew Rabin (1999). "Doing It Now or Later." *American Economic Review*, 89(1), pp. 103-124.

[17] Olivetti, Claudia and M. Daniele Paserman (2013). "In the Name of the Son (and the Daughter): Intergenerational Mobility in the United States, 1850-1930." NBER Working Paper no. 18822.

[18] Phelps, Edmund S. and Robert A. Pollak (1968). "On Second-Best National Saving and Game-Equilibrium Growth." *Review of Economic Studies*, 35(2), pp. 185-199.

[19] Preston, Samuel H. and Michael R. Haines (1991). *Fatal Years: Child Mortality in Late Nineteenth Century America*, Princeton, NJ: Princeton University Press.

[20] Rosenzweig, Mark R. (1988). "Risk, Implicit Contracts and the Family in Rural Areas of Low-income Countries." *Economic Journal*, 98(393), pp. 1148-1170.

[21] Rosenzweig, Mark R. and Oded Stark (1989). "Consumption Smoothing, Migration, and Marriage: Evidence from Rural India." *Journal of Political Economy*, 97(4), pp. 905-926.

[22] Ruggles, Steven J.; Trent Alexander; Katie Genadek; Ronald Goeken; Matthew B. Schroeder, and Matthew Sobek (2010). Integrated Public Use Microdata Series: Version 5.0 [Machine-readable database]. Minneapolis: University of Minnesota.

[23] Solon, Gary R. (1999). "Intergenerational Mobility in the Labour Market," in (O. Ashenfelter and D. Card, eds.), *Handbook of Labor Economics*, Volume 3A, pp. 1761-800, Amsterdam: North-Holland.

[24] Solon, Gary R. (2013). "Theoretical Models of Inequality Transmission Across Multiple Generations." NBER Working Paper no. 18790.

6 Tables

Table 1. Intergenerational Income Elasticities for Three Generations
Levels and Percentile Rank

	(1)	(2)	(3)	(4)	(5)	(6)
Sample:		1860-1880-1900			1850-1880-1910	
Panel A: Log occupational income						
G1		0.6022	0.2568		0.2918	0.1152
		(0.057)	(0.061)		(0.042)	(0.043)
G2 Male	0.2905		0.2679	0.3010		0.2918
	(0.015)		(0.016)	(0.015)		(0.015)
Constant	2.1354	1.2434	1.4582	2.2116	2.2560	1.9047
	(0.043)	(0.164)	(0.165)	(0.045)	(0.121)	(0.122)
Observations	77,883	77,902	77,878	82,060	82,070	82,055
Panel B. Percentile rank of log occupational income						
G1		0.1517	0.0690		0.1286	0.0534
		(0.010)	(0.011)		(0.010)	(0.011)
G2 Male	0.2558		0.2185	0.2650		0.2376
	(0.012)		(0.013)	(0.012)		(0.013)
Constant	2.8396	2.8978	2.8204	2.9456	3.0264	2.9301
	(0.007)	(0.006)	(0.008)	(0.007)	(0.006)	(0.008)
Observations	77,883	77,902	77,878	82,060	82,070	82,055

Note: Panel A contains results from OLS regressions of individual G3 log occupational score on imputed G1 and G2 log occupational score, imputed as the average G1 and G2 log occupational score for each G3 individual's first name. In columns (1)-(3), the G3 sample consists of men age 20-35 in 1900; the G2 sample consists of men age 20-35 in 1880 who have children ages 0-15; the G1 sample consists of men in 1860 who have children ages 0-15. In columns (4)-(6), the samples are constructed similarly, using 30-45 year olds in the 1850, 1880, and 1910 censuses. Panel B contains similar regressions, but percentile ranks of log occupational scores for G1 and G2 are used as explanatory variables; individual G3 log occupational score is still used as the dependent variable. Standard errors are in parentheses.

Table 2. Test of Methodology
Linked IPUMS data

Sample:	(1)	(2)	(3)	(4)	(5)	(6)
		1860-1880-1900			1850-1880-1910	
Panel A: Log occupational income						
G1		0.2417	0.0829		0.1689	0.0933
		(0.069)	(0.063)		(0.048)	(0.045)
G2 Male	0.5268		0.5237	0.4233		0.4208
	(0.022)		(0.022)	(0.017)		(0.017)
Constant	1.3619	2.1940	1.1289	1.8495	2.6031	1.5846
	(0.065)	(0.202)	(0.190)	(0.052)	(0.141)	(0.138)
Observations	2,763	2,763	2,763	4,007	4,007	4,007
Panel B. Percentile rank of log occupational income						
G1		0.1524	0.0300		0.1619	0.0710
		(0.042)	(0.044)		(0.036)	(0.037)
G2 Male	0.4273		0.4183	0.3682		0.3469
	(0.042)		(0.044)	(0.038)		(0.040)
Constant	2.6519	2.8090	2.6394	2.8845	2.9984	2.8540
	(0.026)	(0.027)	(0.032)	(0.023)	(0.023)	(0.028)
Observations	2,763	2,763	2,763	4,007	4,007	4,007

Note: Panel A contains results from OLS regressions of individual G3 log occupational score on G2 log occupa-
tional score and imputed G1 log occupational score, which is imputed as the average G1 log occupational score
for each G2 individual's first name. G3 and G2 data come from the IPUMS linked representative samples from
1880-1900 or 1880-1910; G1 data comes from the 1860 or 1850 IPUMS 1% sample. In columns (1)-(3), the G3
sample consists of men age 20-35 in 1900; the G2 sample consists of men age 20-35 in 1880 who have children
ages 0-15; the G1 sample consists of men in 1860 who have children ages 0-15. In columns (4)-(6), the samples
are constructed similarly, using 30-45 year olds in the 1850, 1880, and 1910 censuses. Panel B contains similar
regressions, but percentile ranks of log occupational scores for G1 and G2 are used as explanatory variables;
individual G3 log occupational score is still used as the dependent variable. Standard errors are in parentheses.

Table 3. Intergenerational Elasticies Across Three Generations:
Percentile Rank Regressions at 20 Year Intervals by gender of G2

VARIABLES	(1)	(2)	(3)	(4)
	G3 Male		G3 Female	
	G2 Male	G2 Female	G2 Male	G2 Female
	Panel A: 1860-1880-1900			
G1	0.0690	0.0106	0.0891	0.0661
	(0.011)	(0.013)	(0.013)	(0.014)
G2	0.2185	0.2659	0.2680	0.3057
	(0.013)	(0.014)	(0.014)	(0.015)
Constant	2.8204	2.8271	2.8492	2.8333
	(0.008)	(0.008)	(0.009)	(0.009)
Observations	77,878	78,634	44,292	44,930
	Panel B: 1880-1900-1920			
G1	0.0967	0.0566	0.0613	0.0944
	(0.010)	(0.011)	(0.011)	(0.012)
G2	0.3300	0.3642	0.3642	0.3602
	(0.012)	(0.012)	(0.011)	(0.012)
Constant	2.8172	2.8163	2.8995	2.8772
	(0.007)	(0.008)	(0.007)	(0.007)
Observations	106,019	107,047	66,324	67,204

Note: Contains results from OLS regressions of individual G3 log occupational score on the percentile rank of imputed G2 and G1 log occupational score, imputed as the average G2 or G1 log occupational score for each G3 individual's first name. For women, log occupational score is measured as the log occupational score of her husband. Panel A uses the 1860-1880-1900 sample, and panel B uses the 1880-1900-1920 sample. The G3 sample consists of adults age 20-35 in 1900 (or 1920); the G2 sample consists of adults age 20-35 in 1880 (or 1900) who have children ages 0-15; the G1 sample consists of men in 1860 (or 1880) who have children ages 0-15. Standard errors are in parentheses.

Table 4. Intergenerational Elasticies Across Three Generations:
Percentile Rank Regressions at 30 Year Intervals by gender of G2

VARIABLES	(1)	(2)	(3)	(4)
	G3 Male		G3 Female	
	G2 Male	G2 Female	G2 Male	G2 Female
	Panel A: 1850-1880-1910			
G1	0.0534	0.0411	0.0227	0.0859
	(0.011)	(0.012)	(0.012)	(0.014)
G2	0.2376	0.2532	0.2823	0.2359
	(0.013)	(0.013)	(0.013)	(0.014)
Constant	2.9301	2.9244	2.9391	2.9269
	(0.008)	(0.009)	(0.009)	(0.009)
Observations	82,055	82,179	55,554	55,631
	Panel B: 1870-1900-1930			
G1	0.0758	0.0393	0.0620	0.0630
	(0.009)	(0.010)	(0.010)	(0.011)
G2	0.2679	0.2971	0.3466	0.3459
	(0.010)	(0.010)	(0.010)	(0.010)
Constant	2.9698	2.9744	2.9618	2.9628
	(0.006)	(0.007)	(0.006)	(0.007)
Observations	114,905	114,949	85,697	85,669

Note: Contains results from OLS regressions of individual G3 log occupational score on the percentile rank of imputed G2 and G1 log occupational score, imputed as the average G2 or G1 log occupational score for each G3 individual's first name. For women, log occupational score is measured as the log occupational score of her husband. Panel A uses the 1850-1880-1910 sample, and panel B uses the 1870-1900-1930 sample. The G3 sample consists of adults age 30-45 in 1910 (or 1930); the G2 sample consists of adults age 30-45 in 1880 (or 1900) who have children ages 0-15; the G1 sample consists of men in 1850 (or 1870) who have children ages 0-15. Standard errors are in parentheses.

Table 5. Intergenerational Elasticies Across Three Generations:
Percentile Rank Regressions with Paternal and Maternal Grandfathers

Panel A: 20-year intervals

VARIABLES	(1)	(2)	(3)	(4)
	1860-1880-1900		1880-1900-1920	
	G3 Male	G3 Female	G3 Male	G3 Female
G1 paternal	0.0823***	0.0724***	0.0899***	0.0455***
	(0.012)	(0.013)	(0.010)	(0.011)
G1 maternal	-0.0178	0.0461***	0.0210*	0.0799***
	(0.013)	(0.014)	(0.011)	(0.012)
G2	0.2053***	0.2544***	0.3195***	0.3222***
	(0.014)	(0.016)	(0.012)	(0.012)
Constant	2.8326***	2.8393***	2.8166***	2.8892***
	(0.008)	(0.010)	(0.008)	(0.008)
Observations	77,503	43,994	105,385	65,970
p (G1 paternal = G1 maternal)	0.000	0.221	0.000	0.055
p (G1 pat [G3 male] = G1 pat [G3 female])	0.585		0.005	
p (G1 mat [G3 male] = G1 mat [G3 female])	0.001		0.000	

Panel B: 30-year intervals

VARIABLES	(1)	(2)	(3)	(4)
	1850-1880-1910		1870-1900-1930	
	G3 Male	G3 Female	G3 Male	G3 Female
G1 paternal	0.0355***	-0.0043	0.0764***	0.0344***
	(0.010)	(0.012)	(0.009)	(0.010)
G1 maternal	0.0306**	0.0612***	0.0030	0.0665***
	(0.012)	(0.014)	(0.010)	(0.011)
G2	0.2218***	0.2453***	0.2655***	0.3191***
	(0.014)	(0.014)	(0.010)	(0.010)
Constant	2.9319***	2.9395***	2.9731***	2.9600***
	(0.009)	(0.010)	(0.007)	(0.007)
Observations	81,061	54,877	113,459	84,533
p (G1 paternal = G1 maternal)	0.776	0.002	0.000	0.055
p (G1 pat [G3 male] = G1 pat [G3 female])	0.015		0.002	
p (G1 mat [G3 male] = G1 mat [G3 female])	0.101		0.000	

Note: Contains results from OLS regressions of individual G3 log occupational score on the percentile rank of imputed scores of G2, paternal G1 and maternal G1; these are imputed as the average for each G3 individual's first name. For women, log occupational score is measured as the log occupational score of her husband. Panel A uses the 1860-1880-1900 and 1880-1900-1920 samples, and panel B uses the 1850-1880-1910 and 1870-1900-1930 samples. The G3 sample consists of adults age 20-35 (or 30-45) in the last sample year; the G2 sample consists of adults age 20-35 (or 30-45) in the second sample year, who have children ages 0-15 and are married to spouse in the same age bracket; the G1 sample consists of men in the first sample year who have children ages 0-15. Standard errors are in parentheses.

Table 6. Intergenerational Elasticies Across Three Generations:
Percentile Rank Regressions with Paternal and Maternal Grandfathers using Alternative Occupational Rankings

Panel A: 1900 wage distribution

VARIABLES	(1) 1860-1880-1900 G3 Male	(2) 1860-1880-1900 G3 Female	(3) 1880-1900-1920 G3 Male	(4) 1880-1900-1920 G3 Female	(5) 1850-1880-1910 G3 Male	(6) 1850-1880-1910 G3 Female	(7) 1870-1900-1930 G3 Male	(8) 1870-1900-1930 G3 Female
G1 paternal	0.0488***	0.0369***	0.0658***	0.0462***	0.0740***	0.0072	0.0624***	0.0669***
	(0.009)	(0.011)	(0.007)	(0.009)	(0.008)	(0.010)	(0.007)	(0.008)
G1 maternal	-0.0030	0.0254**	0.0016	0.0534***	0.0360***	0.0206**	-0.0019	0.0602***
	(0.011)	(0.012)	(0.008)	(0.010)	(0.009)	(0.010)	(0.008)	(0.009)
Observations	78,525	44,036	110,483	66,561	82,361	55,313	115,717	85,396
p (G1 paternal = G1 maternal)	0.002	0.524	0.000	0.604	0.004	0.360	0.000	0.625
p (G1 pat [G3 male] = G1 pat [G3 female])	0.418		0.090		0.000		0.683	
p (G1 mat [G3 male] = G1 mat [G3 female])	0.096		0.000		0.278		0.000	

Panel B: Wage distribution based on adjusted average personal property by occupation in 1860 and 1870

VARIABLES	(1) 1860-1880-1900 G3 Male	(2) 1860-1880-1900 G3 Female	(3) 1880-1900-1920 G3 Male	(4) 1880-1900-1920 G3 Female	(5) 1850-1880-1910 G3 Male	(6) 1850-1880-1910 G3 Female	(7) 1870-1900-1930 G3 Male	(8) 1870-1900-1930 G3 Female
G1 paternal	0.1902***	0.1528***	0.2171***	0.1719***	0.2241***	0.1404***	0.2753***	0.1858***
	(0.023)	(0.031)	(0.020)	(0.025)	(0.023)	(0.026)	(0.023)	(0.027)
G1 maternal	0.1603***	0.1614***	0.0855***	0.1387***	0.1526***	0.0827***	0.0163	0.1526***
	(0.025)	(0.033)	(0.024)	(0.027)	(0.024)	(0.026)	(0.026)	(0.027)
Observations	76,875	43,780	98,371	63,586	78,252	53,525	107,954	81,271
p (G1 paternal = G1 maternal)	0.464	0.874	0.000	0.423	0.052	0.148	0.000	0.461
p (G1 pat [G3 male] = G1 pat [G3 female])	0.336		0.158		0.016		0.012	
p (G1 mat [G3 male] = G1 mat [G3 female])	0.980		0.136		0.050		0.000	

Note: Contains results from OLS regressions of individual G3 log occupational score on the percentile rank of imputed scores of G2, paternal G1 and maternal G1; these are imputed as the average for each G3 individual's first name. For women, log occupational score is measured as the log occupational score of her husband. Panel A measures occupational income using the 1900 wage distribution with an imputed wage for farmers (Preston and Haines 1991; Abramitzky et al 2012; Olivetti and Paserman 2013). Panel B measures occupational income using mean personal wealth by occupation in 1860 and 1870, adjusting the wealth of farmers downward by the average value of farm equipment and livestock (values from Haines and ICPSR 2010). The G3 sample consists of adults age 20-35 (or 30-45) in the last sample year; the G2 sample consists of adults age 20-35 (or 30-45) in the second sample year, who have children ages 0-15 and are married to spouse in the same age bracket; the G1 sample consists of men in the first sample year who have children ages 0-15. Standard errors are in parentheses.

Table 7. Intergenerational Elasticies Across Three Generations:
Percentile Rank Regressions with Paternal and Maternal Grandfathers Excluding Regions

Panel A: Excluding the northeast

VARIABLES	(1) G3 Male	(2) G3 Female	(3) G3 Male	(4) G3 Female	(5) G3 Male	(6) G3 Female	(7) G3 Male	(8) G3 Female
	1860-1880-1900		1880-1900-1920		1850-1880-1910		1870-1900-1930	
G1 paternal	0.0828***	0.0069	0.0369***	0.0696***	0.0304**	-0.0141	0.0598***	0.0622***
	(0.013)	(0.016)	(0.012)	(0.013)	(0.013)	(0.014)	(0.011)	(0.012)
G1 maternal	0.0397**	0.0549***	0.0207	0.0736***	0.0443***	0.1110***	0.0065	0.0588***
	(0.016)	(0.017)	(0.013)	(0.014)	(0.014)	(0.016)	(0.012)	(0.014)
Observations	52,050	30,265	72,100	46,358	53,939	36,530	76,786	57,416
p (G1 paternal = G1 maternal)	0.061	0.058	0.415	0.844	0.509	0.000	0.005	0.864
p (G1 pat [G3 male] = G1 pat [G3 female])	0.000		0.079		0.022		0.885	
p (G1 mat [G3 male] = G1 mat [G3 female])	0.526		0.008		0.002		0.005	

Panel B: Excluding the midwest

VARIABLES	(1) G3 Male	(2) G3 Female	(3) G3 Male	(4) G3 Female	(5) G3 Male	(6) G3 Female	(7) G3 Male	(8) G3 Female
	1860-1880-1900		1880-1900-1920		1850-1880-1910		1870-1900-1930	
G1 paternal	0.0966***	0.0826***	0.1155***	0.0718***	0.0421***	0.0087	0.1112***	0.0744***
	(0.014)	(0.017)	(0.012)	(0.015)	(0.013)	(0.015)	(0.010)	(0.012)
G1 maternal	-0.0237	0.1202***	0.0580***	0.1176***	0.0927***	0.0481***	0.0786***	0.0678***
	(0.015)	(0.017)	(0.013)	(0.014)	(0.014)	(0.016)	(0.012)	(0.013)
Observations	47,137	26,091	65,647	40,981	51,281	34,027	71,879	53,241
p (G1 paternal = G1 maternal)	0.000	0.137	0.007	0.036	0.012	0.099	0.069	0.729
p (G1 pat [G3 male] = G1 pat [G3 female])	0.524		0.027		0.101		0.021	
p (G1 mat [G3 male] = G1 mat [G3 female])	0.000		0.002		0.033		0.531	

Panel C: Excluding the south

VARIABLES	(1) G3 Male	(2) G3 Female	(3) G3 Male	(4) G3 Female	(5) G3 Male	(6) G3 Female	(7) G3 Male	(8) G3 Female
	1860-1880-1900		1880-1900-1920		1850-1880-1910		1870-1900-1930	
G1 paternal	0.0377***	0.0643***	0.0727***	0.0194	0.0059	-0.0082	0.0698***	0.0105
	(0.012)	(0.014)	(0.011)	(0.012)	(0.011)	(0.013)	(0.009)	(0.011)
G1 maternal	-0.0035	-0.0087	0.0537***	0.0304**	-0.0166	-0.0063	-0.0509***	0.0202*
	(0.013)	(0.014)	(0.012)	(0.012)	(0.013)	(0.014)	(0.010)	(0.011)
Observations	59,987	32,966	80,471	48,828	63,644	42,448	88,447	64,851
p (G1 paternal = G1 maternal)	0.035	0.001	0.257	0.530	0.212	0.926	0.000	0.567
p (G1 pat [G3 male] = G1 pat [G3 female])	0.160		0.002		0.419		0.000	
p (G1 mat [G3 male] = G1 mat [G3 female])	0.796		0.180		0.589		0.000	

Note: Contains results from OLS regressions of individual G3 log occupational score on the percentile rank of imputed scores of G2, paternal G1 and maternal G1; these are imputed as the average for each G3 individual's first name. For women, log occupational score is measured as the log occupational score of her husband. Panel A excludes observations from the Northeast; panel B excludes observations from the Midwest; and panel C excludes observations from the South. The G3 sample consists of adults age 20-35 (or 30-45) in the last sample year; the G2 sample consists of adults age 20-35 (or 30-45) in the second sample year, who have children ages 0-15 and are married to spouse in the same age bracket; the G1 sample consists of men in the first sample year who have children ages 0-15. Standard errors are in parentheses.

A Intergenerational Time Inconsistency: Details and Proofs

Here, we provide details of the model discussed in Section 4.1.

We label the optimal consumption choices made by the agent in the commitment and sophistication regime $\left\{c_t^{COMM}\right\}_{t=1}^3$ and $\left\{c_t^{SOPH}\right\}_{t=1}^3$, respectively. The resulting income levels are $\left\{Y_t^{COMM}\right\}_{t=1}^3$ and $\left\{Y_t^{SOPH}\right\}_{t=1}^3$.

The following proposition holds:

Proposition 1. *(a) If G1 can commit to all future decisions, the incomes of G2 and G3 will be, respectively*

$$Y_2^{COMM} = \frac{R\beta\delta\left(1+\delta\right)}{1+\beta\delta+\beta\delta^2}Y_1$$

and

$$Y_3^{COMM} = \frac{R^2\beta\delta^2}{1+\beta\delta+\beta\delta^2}Y_1;$$

(b) If G1 cannot commit to all future decisions, the incomes of G2 and G3 will be, resepctively

$$Y_2^{SOPH} = \frac{R\beta\delta\left(1+\delta\right)}{1+\beta\delta+\beta\delta^2}Y_1$$

and

$$Y_3^{SOPH} = \frac{R^2\beta^2\delta^2\left(1+\delta\right)}{\left(1+\beta\delta+\beta\delta^2\right)\left(1+\beta\delta\right)}Y_1.$$

Proof. When G1 can commit to all future resource allocations, he solves the following maximization problem:

$$\max_{c_1,c_2,c_3}\ln(c_1)+\beta\delta\ln(c_2)+\beta\delta^2\ln(c_3)\quad\text{s.t.}\quad Y_1=c_1+\frac{c_2}{R}+\frac{c_3}{R^2}$$

This generates the following optimal choices of c_1, c_2, and c_3:

$$c_1 = \frac{1}{1+\beta\delta+\beta\delta^2}Y_1$$
$$c_2 = \frac{\beta\delta R}{1+\beta\delta+\beta\delta^2}Y_1$$
$$c_3 = \frac{\beta\delta^2 R^2}{1+\beta\delta+\beta\delta^2}Y_1$$

Part (a) follows from the fact that $Y_3 = c_3$ and $Y_2 = c_2 + \frac{Y_3}{R}$.

When G1 cannot commit to future resource allocations, he will anticipate G2's resource allocation decision and make his decisions accordingly. Taking Y_2 as given, G2 will solve the following:

$$\max_{c_2, c_3} \ln(c_2) + \beta\delta \ln(c_3) \quad \text{s.t.} \quad Y_2 = c_2 + \frac{c_3}{R}$$

The solution to this problem yields the following optimal choices of c_2 and c_3:

$$c_2 = \frac{1}{1 + \beta\delta} Y_2$$

$$c_3 = \frac{\beta\delta R}{1 + \beta\delta} Y_2$$

Then, G1's optimization problem can be written:

$$\max_{c_1, Y_2} \ln(c_1) + \beta\delta \ln\left(\frac{Y_2}{1 + \beta\delta}\right) + \beta\delta^2 \ln\left(\frac{\beta\delta R Y_2}{1 + \beta\delta}\right) \quad \text{s.t.} \quad Y_1 = c_1 + \frac{Y_2}{R}$$

The solution to this problem for Y_2 is

$$Y_2 = \frac{R\beta\delta(1 + \delta)}{1 + \beta\delta + \beta\delta^2} Y_1$$

The value of Y_3 follows from the solution for c_3 given above, and from the fact that $Y_3 = c_3$. □

This result allows one to calculate the relationship between the incomes of the different generations. Let $\eta_{2,1}$ and $\eta_{3,1}$ be, respectively, the slope coefficients in regressions of Y_2 and Y_3 on Y_1. It follows directly from the proposition that $\eta_{2,1}^{SOPH} = \eta_{2,1}^{COMM}$ and $\eta_{3,1}^{SOPH} < \eta_{3,1}^{COMM}$.

B Multi-trait Matching and Inheritance: Details

Based on our assumptions and marriage market equilibrium, we obtain the following two-generation transition probability matrices.

$$\Pi_M = \begin{bmatrix} \left(1-\pi_x^M\right)\left(1-\pi_y^M\right) & \pi_x^M\left(1-\pi_y^M\right) & \left(1-\pi_x^M\right)\pi_y^M & \pi_x^M\pi_y^M \\ \pi_x^M\left(1-\pi_y^M\right) & \left(1-\pi_x^M\right)\left(1-\pi_y^M\right) & \pi_x^M\pi_y^M & \left(1-\pi_x^M\right)\pi_y^M \\ \left(1-\pi_x^M\right)\pi_y^M & \pi_x^M\pi_y^M & \left(1-\pi_x^M\right)\left(1-\pi_y^M\right) & \pi_x^M\left(1-\pi_y^M\right) \\ \pi_x^M\pi_y^M & \left(1-\pi_x^M\right)\pi_y^M & \pi_x^M\left(1-\pi_y^M\right) & \left(1-\pi_x^M\right)\left(1-\pi_y^M\right) \end{bmatrix}$$

$$\Pi_F = \begin{bmatrix} \left(1-\pi_x^F\right)\left(1-\pi_y^F\right) & \left(1-\pi_x^F\right)\pi_y^F & \pi_x^F\left(1-\pi_y^F\right) & \pi_x^F\pi_y^F \\ \left(1-\pi_x^F\right)\pi_y^F & \left(1-\pi_x^F\right)\left(1-\pi_y^F\right) & \pi_x^F\pi_y^F & \pi_x^F\left(1-\pi_y^F\right) \\ \pi_x^F\left(1-\pi_y^F\right) & \pi_x^F\pi_y^F & \left(1-\pi_x^F\right)\left(1-\pi_y^F\right) & \left(1-\pi_x^F\right)\pi_y^F \\ \pi_x^F\pi_y^F & \pi_x^F\left(1-\pi_y^F\right) & \left(1-\pi_x^F\right)\pi_y^F & \left(1-\pi_x^F\right)\left(1-\pi_y^F\right) \end{bmatrix}$$

Intergenerational correlations corresponding to the matrices $\Omega_{M,PAT}, \Omega_{M,MAT}, \Omega_{F,PAT}$ and $\Omega_{F,MAT}$:

$$
\begin{aligned}
\rho_{M,PAT} &= 1 - \frac{4}{5}\pi_x^M\left(1-\pi_x^M\right) - \frac{16}{5}\pi_y^M\left(1-\pi_y^M\right) \\
\rho_{M,MAT} &= \rho_{F,PAT} = 1 - \frac{4}{5}\pi_x^M\left(1-\pi_x^M\right) - \frac{16}{5}\pi_y^M\left(1-\pi_y^M\right) \\
&\quad - \frac{2}{5}\left(\pi_y^F - \pi_x^M\right)\left(1-2\pi_x^M\right) - \frac{8}{5}\left(\pi_x^F - \pi_y^M\right)\left(1-2\pi_y^M\right) \\
&= 1 - \frac{4}{5}\pi_y^F\left(1-\pi_y^F\right) - \frac{16}{5}\pi_x^F\left(1-\pi_x^F\right) \\
&\quad - \frac{2}{5}\left(\pi_x^M - \pi_y^F\right)\left(1-2\pi_y^F\right) - \frac{8}{5}\left(\pi_y^M - \pi_x^F\right)\left(1-2\pi_x^F\right) \\
\rho_{F,MAT} &= 1 - \frac{4}{5}\pi_y^F\left(1-\pi_y^F\right) - \frac{16}{5}\pi_x^F\left(1-\pi_x^F\right)
\end{aligned}
$$

Note that because all the switching probabilities are bounded between 0 and $1/2$, the correlations $\rho_{M,PAT}$ and $\rho_{F,MAT}$ are necessarily greater than zero. On the other hand, $\rho_{M,MAT}$ and $\rho_{F,PAT}$ can be either positive or negative, depending on the exact values of the $\pi's$.

Table A1. Intergenerational Income Elasticities across Three Generations, 1860-1880-1900
Different Sample Restrictions for G2 and G3

	VARIABLES	G2: Baseline				G2: Married to spouse ages 20-35			
		G3 Male	G3 Female	G3 Male	G3 Female	G3 Male	G3 Female	G3 Male	G3 Female
G3: Baseline	G1	0.0690	0.0891	0.0106	0.0661	0.0798	0.0072	0.0817	0.0646
		(0.011)	(0.013)	(0.013)	(0.014)	(0.011)	(0.012)	(0.013)	(0.014)
	G2 Male	0.2185	0.2680			0.2007	0.2494		
		(0.013)	(0.014)			(0.013)	(0.013)		
	G2 Female			0.2659	0.3057			0.2768	0.2710
				(0.014)	(0.015)			(0.014)	(0.015)
	Constant	2.8204	2.8492	2.8271	2.8333	2.8252	2.8397	2.8487	2.8585
		(0.008)	(0.009)	(0.008)	(0.009)	(0.008)	(0.008)	(0.009)	(0.009)
	Observations	77,878	44,292	78,634	44,930	77,718	77,761	44,171	44,168
G3: Married	G1	0.0938	0.0891	0.0728	0.0661	0.1051	0.0817	0.0639	0.0646
		(0.015)	(0.013)	(0.017)	(0.014)	(0.015)	(0.013)	(0.017)	(0.014)
	G2 Male	0.2426	0.2680			0.2262	0.2768		
		(0.018)	(0.014)			(0.018)	(0.014)		
	G2 Female			0.2759	0.3057			0.2655	0.2710
				(0.019)	(0.015)			(0.017)	(0.015)
	Constant	2.8530	2.8492	2.8481	2.8333	2.8565	2.8487	2.8608	2.8585
		(0.010)	(0.009)	(0.011)	(0.009)	(0.010)	(0.009)	(0.011)	(0.009)
	Observations	35,500	44,292	35,827	44,930	35,434	44,171	35,449	44,168
G3: Married to spouse ages 20-35	G1	0.0959	0.0775	0.0700	0.0739	0.1065	0.0717	0.0581	0.0721
		(0.016)	(0.016)	(0.019)	(0.017)	(0.016)	(0.016)	(0.018)	(0.017)
	G2 Male	0.2302	0.2694			0.2139	0.2776		
		(0.019)	(0.017)			(0.019)	(0.017)		
	G2 Female			0.2617	0.2926			0.2557	0.2608
				(0.020)	(0.018)			(0.019)	(0.018)
	Constant	2.8701	2.8533	2.8690	2.8348	2.8742	2.8522	2.8809	2.8585
		(0.011)	(0.011)	(0.012)	(0.011)	(0.011)	(0.011)	(0.012)	(0.011)
	Observations	29,295	29,550	29,563	29,957	29,238	29,469	29,252	29,453

Table A2. Summary of G1-G3 Intergenerational Income Elasticities using Different Sample Restrictions and Wage Measures
Percentile Rank Regressions

Dependent variable:	Intergenerational income elasticity: G1-G3				
	All	G3 Male	G3 Female	G2 Male	G2 Female
G2 Male	0.0048	0.0312***	-0.0217*		
	(0.009)	(0.006)	(0.011)		
G3 Male	0.0056			0.0320***	-0.0209**
	(0.009)			(0.009)	(0.007)
Year (G2)=1900	0.0169*	0.0221***	0.0117	0.0196*	0.0142*
	(0.009)	(0.006)	(0.011)	(0.009)	(0.007)
Interval = 30 years	-0.0239**	-0.0260***	-0.0218*	-0.0347***	-0.0130
	(0.009)	(0.006)	(0.011)	(0.009)	(0.007)
Specification details:					
G2 spouse in same age bracket	-0.0048*	-0.0038	-0.0058	-0.0036	-0.0060
	(0.003)	(0.003)	(0.004)	(0.004)	(0.004)
G3 married	0.0145***	0.0290***		0.0108*	0.0181*
	(0.005)	(0.006)		(0.005)	(0.009)
G3 spouse in same age bracket	0.0131**	0.0237**	0.0025	0.0097*	0.0166*
	(0.005)	(0.007)	(0.003)	(0.005)	(0.008)
Constant	0.0605***	0.0425***	0.0841***	0.0579***	0.0679***
	(0.012)	(0.011)	(0.013)	(0.014)	(0.010)
Observations	96	48	48	48	48