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Daniel S. Hamermesh
University of Texas at Austin, IZA and NBER

Anwen Zhang
University of Glasgow

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IZA – Institute of Labor Economics

Schaumburg-Lippe-Straße 5–9
53113 Bonn, Germany

Phone: +49-228-3894-0
Email: publications@iza.org

www.iza.org

ABSTRACT

The Economic Impact of Heritable Physical Traits: Hot Parents, Rich Kid?*

Since the mapping of the human genome in 2004, biologists have demonstrated genetic links to the expression of several income-enhancing physical traits. To illustrate how heredity produces intergenerational economic effects, this study uses one trait, beauty, to infer the extent to which parents' physical characteristics transmit inequality across generations. Analyses of a large-scale longitudinal dataset in the U.S., and a much smaller dataset of Chinese parents and children, show that a one standard-deviation increase in parents' looks is associated with a 0.4 standard-deviation increase in their child's looks. A large data set of U.S. siblings shows a correlation of their beauty consistent with the same expression of their genetic similarity, as does a small sample of billionaire siblings. Coupling these estimates with parameter estimates from the literatures describing the impact of beauty on earnings and the intergenerational elasticity of income suggests that one standard-deviation difference in parents' looks generates a 0.06 standard-deviation difference in their adult child's earnings, which amounts to additional annual earnings in the U.S. of about $2300.

JEL Classification: D64, D31, J71

Keywords: intergenerational transmission, inequality, beauty

Corresponding author:
Daniel S. Hamermesh
University of Texas at Austin
110 Inner Campus Drive
Austin, TX 78705
USA

E-mail: hamermes@eco.utexas.edu

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"…the conversation between Isadora Duncan and Anatole France, who were discussing eugenics, came to a sudden stop when Isadora said: 'Imagine a child with my beauty and your brains!' and Anatole responded: 'Yes, but imagine a child with my beauty and your brains!'"
https://quoteinvestigator.com/2013/04/19/brains-beauty/

I. Introduction

An immense literature has examined intergenerational income mobility—the relationship between the position in the income distribution of parents in Generation t-1 and that of their child(ren) in Generation t. The amount of interest in this issue is unsurprising: It ties to the most central questions underlying social relations, as discussed in fundamentally opposing ways by Rawls (1971) and Nozick (1974). Modern empirical analyses for the U.S. go back at least to Solon (1992), but follow-up studies continue to this day. (Solon, 2002; Lee and Solon, 2009; Chetty and Hendren, 2018; Justman and Stiassnie, 2021; Siminski and Yu, 2022; and Berman, 2022, are just a few in this continuously burgeoning literature.)

Related literatures have examined the extent to which individual parental behaviors and outcomes are transmitted across generations. These have included studies of education (Currie and Moretti, 2003); mental health (Bütikofer *et al*., 2023); and preferences (Dohmen *et al*., 2012; Doepke and Zilibotti, 2017; Cobb-Clark *et al*., 2019; Chowdhury *et al*., 2022; and Brenoe and Epper, 2023). Presumably this transmission partly underlies intergenerational correlations of incomes, although in these studies the mechanisms by which it does so are in some "black box" linking generations.

Becker and Tomes (1979) demonstrated that a sensible model of the intergenerational transmission of incomes must be based on the transmission of characteristics that are partly genetically determined. As of the turn of the 21st century, however, one could not argue convincingly for the existence of genetic differences leading to correlations of any characteristics underlying intergenerational economic mobility. An immense literature has tried to tease out answers to the nature vs. nurture question, with Taubman (1976) an early example of the many modern economic studies that have relied on differences between mono- and dizygotic twins to provide answers. As Kamin (1974) demonstrated, however, twins' models do not allow the nature-nurture distinction to be made so easily as first glances would suggest, rendering uncertain any claims for genetic links of these traits.

With the mapping of the human genome (International Human Genome Sequencing Consortium, 2004), geneticists have now found specific genes that, taken together, are related to expressions of potentially income-enhancing physical characteristics that may be correlated across generations. In what follows we thus describe and apply a way of calculating how a physical trait that has now been demonstrated to be partly heritable contributes to intergenerational inequality, using the example of human beauty. Because the central empirical focus is on measuring the heritability of looks, which does not seem to have been done before, we use four different datasets—two large longitudinal surveys and two small datasets, to infer the magnitude of this parameter.

Section II outlines how the impact of a heritable trait in Generation t-1 can affect incomes in Generation t. Section III describes the main source of data used to estimate the relationship of parents' and children's beauty, presents the analysis of those data, and offers a brief examination of the same issue using a much sparser data set. Section IV approaches heritability in an alternative way, examining the correlation of beauty among siblings, first on a large national survey of adolescents, then using a small sample of billionaire siblings. Section V applies the estimates of the heritability of beauty, along with existing estimates of the intergenerational correlation of incomes and of the impact of beauty on earnings, to infer the total effect of beauty in one generation on income in the next. The concluding section outlines some other traits for which genetic bases have now been established and thus which could be analyzed using the framework presented here.

II. Inferring the Intergenerational Impact of a Heritable Trait

A. Background to the Estimation

Consider a heritable trait H, embodied in Generation t-1 and transmitted to Generation t, which increases the income of those who possess it. In the context of the intergenerational transmission of inequality, the income of a member of Generation t is a function of the extent to which income is transmitted across the generations, β_1, and the income-increasing value β_2 of their expression of the trait:

(1) $Y_t = \beta_0 + \beta_1 Y_{t-1} + \beta_2 H_t$,

where Y is the logarithm of income, the β are parameters, and where other determinants of Y_t that are uncorrelated with Y_{t-1} and H_t are ignored.

While both parameters in (1) have been estimated separately many times, no study has examined whether Y_{t-1} and H_t have independent effects on an individual's current income (or earnings). To study this precursor to answering the central question of this article, we estimate (1) over the two datasets that provide information on all three variables. The first is the Wisconsin Longitudinal Study *(*WLS*,* see Herd *et al.*, 2014), a random sample of 1957 Wisconsin high-school graduates. These respondents have been followed since 1957, including in 1966 when their parents' household income was obtained, and 1992-93, when information on their household income was gathered. In the early 2000s a group of 12 adults of roughly the same age cohort independently rated the high-school graduation pictures of the sample members. The raters' scores were averaged and unit-normalized, yielding a measure of H. To estimate (1), we created indicators for attractive faces (the top one-third of ratings) and unattractive faces (the bottom one-sixth of ratings).

The other usable survey for estimating (1) is the National Longitudinal Study of Adolescent to Adult Health (Add Health, Billy *et al*., 1998), a school-based longitudinal study of a nationally representative sample of adolescents in grades 7–12 in the United States during the 1994–95 school year. Add Health combines longitudinal survey data on respondents' social and economic characteristics. Afterward the Study conducted a series of more detailed in-home interviews with a stratified random sub-sample of the students, resulting in a representative sample of adolescents in grades 7–12 in the Wave I in-home survey in 1994-95, of whom 15,701 were included in Wave IV in 2008-09. Immediately after each of the in-home interviews the interviewer rated the subject's beauty, responding on a 5 to 1 scale (very attractive, attractive, about average, unattractive, very unattractive) to the question, "How physically attractive is the respondent?" Here we treat those rated 4 or 5 as attractive, those rated 1 or 2 as unattractive. Their parents' household income in 1994 was obtained, as was their household income in 2007.

The first and fourth columns of Table 1 show means of the variables; the estimates in the second and fifth columns show the intergenerational income elasticity (IIE) alone, while the third and sixth columns add the beauty measures to the equation, thus fully specifying (1). We focus here on men only, which is common in the literature on the IIE. The estimated IIE in both samples is about 0.25, somewhat lower than found in the literature generally. Being in the left tail of the distribution of looks significantly lowers income, while there is some indication that being above-average in looks raises income (in the ADD Health only). The crucial finding, however, is that the estimates of the IIE in both samples change only minutely when the beauty measures are added. Parental income Y_{t-1} and own beauty H_t have essentially independent impacts on one's income. Note that this evidence does not answer the central question of whether and to what extent *parental* beauty H_{t-1} contributes to children's income, which we elaborate below. It does, however, justify our approach of gathering and synthesizing evidence on β_1 and β_2 separately from two very distinct literatures and using it in conjunction with our novel estimates.

B. Deriving the Central Estimating Equation

Differentiating in (1) totally with respect to H_{t-1}:

(2) $dY_t/dH_{t-1} = \beta_1[\partial Y_{t-1}/\partial H_{t-1}]_{Ht} + \beta_2[\partial H_t/\partial H_{t-1}]_{Yt-1}$.

The first term is the indirect effect of the parents' expression of the trait on child's income through its effect on the parents' income; the second term is the direct effect on his/her income arising from his/her expression of the inherited trait. Even if $\beta_1 = 0$—one's income is unaffected by one's parents' income, the IIE is zero—the inherited trait still gives the child an economic advantage through the direct effect. Essentially Equation (2) decomposes the effect of H_{t-1} indirectly through the parents' income and directly through its impact on the child's success.

Assuming that the effect of the trait on earnings is the same across generations, rewrite (2) as:

(2') $dY_t/dH_{t-1} = \beta_1\beta_2 + \beta_2[\partial H_t/\partial H_{t-1}]$.

Since estimates of $\partial H_t/\partial H_{t-1}$ do not exist, producing them is the central focus of the empirical analysis. We use the estimates of the intergenerational transmission of beauty along with consensus estimates of the parameters β_1 and β_2 to infer the extent to which a heritable trait contributes to income inequality in a subsequent generation and to which it accounts for the commonly observed correlations of incomes across generations.

Is beauty a good example of H? As the epigraph indicates, people have long believed that it is, well before there was any demonstration of a scientific basis for that belief (although the epigraph shows some uncertainty about the expression of any hereditary beauty). Several studies, however, now demonstrate this to be the case among humans (Mitchem *et al*., 2014; Sasaki *et al*., 2018; Hu *et al*., 2019; and White and Puts, 2019), showing that physical attractiveness is correlated with the presence of various genes. Of course, the cause of differences in human physical attractiveness is not any specific gene or group of genes; and perceptions of human beauty can be modified, albeit slightly, by efforts, including spending, to improve one's appearance (Hamermesh *et al*., 2002, for weak evidence, and Etcoff *et al*., 2011, for stronger evidence). We now know, however, that there is some genetic basis for claiming that beauty is heritable, thus justifying using it as an example to infer the role of a heritable physical trait in transmitting income inequality.

III. Measuring the Heritability of Beauty—Parents and Children

A. Data on Beauty on the SECCYD

Data on the beauty of members of two generations are contained in the Study of Early Child Care and Youth Development (SECCYD). The SECCYD was a longitudinal survey that began with a sample of 1,364 infants born in hospitals in 10 U.S. locations in 1990. The children were evaluated along various criteria, particularly on their social and cognitive achievements, at ages 6 months (Wave 1) up through adolescence (age 15) in Wave 11, and their parents' demographic and economic characteristics at Wave 1 were recorded. Videos of the children engaged in various activities were made at each Wave; and at Waves 1, 7 (3rd grade), 9 (5th grade), and Wave 11 a video of the child engaged in some activity with her/his mother was made. (See Gordon *et al*., 2020, for a detailed description of the creation and use of the videos.)

Each of the videos was edited into short slices, 7 to 10 seconds long, with the slices then edited so that the child and the mother appear separately.[1] At two universities undergraduate students, who were

[1]Using short slices of videos for this purpose was pioneered by Ambady and Rosenthal (1992) and was employed in economic analyses by Benjamin and Shapiro (2009).

roughly of the same birth cohort as the subjects of the SECCYD, rated the looks of the children and mothers on a 5 to 1 scale (very attractive to very unattractive), in response to the question, "How attractive (cute) is the child/adolescent/mother overall?" The empirical analysis here includes only those children and mothers, both of whose attractiveness was evaluated by at least 10 raters.[2]

We pool observations of the child's and mother's beauty in Waves 9 and 11 of the SECCYD. The requirements on the number of raters reduced the sample from 1,877 to 1,737. Some of the women accompanying the children were not clearly the biological mother. To ensure that we are measuring inheritance, we exclude those child-mother pairs, along with one pair for which data on the covariates that are used to adjust for possible differences in the average ratings were not available, resulting in a usable sample of 1,378 child-mother pairs. Of these pairs, 590 appear in both Waves 9 and 11, and 198 appear in only one of the two waves.

B. Main Estimates from the SECCYD

To estimate equations describing the transmission of the trait, let G_t be the child's genetic endowment, and G^M_{t-1} and G^F_{t-1} be the mother's and father's endowments. Write the child's genes related to beauty as a function of its parents' genes:

$$(3)\quad G_t = F(G^M_{t-1}, G^F_{t-1}) .$$

We cannot observe the genetic endowment of either the child or its parents. We might, however, observe the beauty of each, which can be viewed as the expressions of those endowments, so that we can write the child's beauty as:

$$(3')\quad B_t = \alpha_1 B^M_{t-1} + \alpha_2 B^F_{t-1} + \varepsilon_t ,$$

where the B are measures of the parents' and child's beauty, the α are parameters to be estimated and the error term ε_t accounts for the fact that the child's beauty depends upon more than its parents' observed beauty.

[2]Gordon *et al*. (2013) and Hamermesh *et al*. (2023) linked the ratings of the children's looks to the measures of their cognitive and other skills.

Unfortunately, the SECCYD does not contain assessments of fathers' looks, so we cannot estimate Equation (3') with these data. To solve the problem of missing assessments of the father's looks, since each parent contributes half the child's genes that contribute to producing her/his beauty, by assumption $\alpha_1 = \alpha_2 = \alpha$, so that 2α measures the expression of inherited beauty. If beauty were like simply determined inherited characteristics, such as eye color, red-green color blindness, blood type, etc., so that we knew the parents' genotypes exactly, we would expect $\alpha = 0.5$. This determinacy is obviously not the case with beauty, so that we should expect to observe $\alpha < 0.5$. The null hypothesis is that $\alpha = 0$, i.e., that the expression of any genetic basis of beauty is not discernable.

Assuming assortative mating among parents along the dimension of beauty, their looks are correlated according to ρ_{MF}. Substantial evidence shows the presence of positive assortative dating/mating along the dimension of looks (e.g., Berscheid *et al*., 1971, an early example; Epstein and Gutmann, 1984, a meta-analysis), so that $1 \geq \rho_{MF} > 0$.[3] Writing $B^F_{t-1} = \rho_{MF} B^M_{t-1}$ and substituting into (3'):

(4) $B_t = \alpha[1 + \rho_{MF}]B^M_{t-1} + \varepsilon_t$.

One additional difficulty is that this equation ignores the possible impacts of covariates on perceptions of the child's and the mother's looks. One vector of covariates, X, might affect ratings of children's looks, while another, Z, might affect ratings of their mothers' looks. To account for these possibilities, we purge both B_t and B^M_{t-1} by regressing each on subsets of the available covariates in the SECCYD, obtaining the residuals B^*_t and B^{*M}_{t-1}. The final equation is:

(5) $B^*_t = \alpha[1 + \rho_{MF}]B^{*M}_{t-1} = \alpha^* B^{*M}_{t-1} + \varepsilon_t$,

with α^* the parameter estimated in this simple bivariate regression. With assumptions on the magnitude of ρ_{MF}, we can bracket the total effect of parents' looks on those of the child, 2α, between α^* and $2\alpha^*$.

The average rating of children's looks in Waves 9 and 11 was 2.98 on the 5 to 1 scale (s.d. = 0.61), that of their mothers was 2.81 (s.d. = 0.57). Table 2 presents statistics describing the SECCYD sample.

[3]Calculations using data from Shanghai in 1996 (Hamermesh *et al*., 2002) show a correlation of husbands' and wives' looks of 0.61 among 761 couples with partners ages 22-60. The positive correlation is consistent with evidence on subjects' choices of photographs of opposite-sex members (Laeng *et al*., 2013).

While their mothers' looks are unsurprisingly rated the same regardless of the child's gender, boys' looks are rated significantly below those of girls. Given those averages, however, the average standard errors within groups of raters of each child are the same by gender. 89 percent of raters viewed the videos that they evaluated as sufficiently light to make them confident in their ratings, and slightly under half of the videos yielded pictures that no raters viewed as grainy.

The SECCYD also provides information on other characteristics of the child and mother, including the child's race/ethnicity, the mother's education, and her age when the child entered the study (thus 10 years below her age at Wave 9, 15 years below her age at Wave 11). The Survey provides no information on the household's income, but a rough measure, its income/needs ratio, is available. We construct indicators of race (African American, or not) and ethnicity (Hispanic or not), indicators of mother's education, and quartiles of the income/needs ratios to constitute the vector X. The vector Z contains the same measures but adds the mother's age. The mothers in the sample are better educated than was the average American woman in 1990; the children are less likely to be African American, but about equally likely to be Hispanic, as the 1990 U.S. population. The averages of the components of X and Z do not differ greatly between girls and boys.

Figures 1a and 1b present scatters and regression lines fitting B_t to B^M_{t-1} separately for girls and boys. With the average rating for boys being below that for girls, the intercept is lower in Figure 1b than in Figure 1a. One crucial thing to note, however, is that the slopes imply a significant relationship between the child's and mother's looks. Moreover, the slopes are not distinguishable statistically from each other. Also, the slopes are steeper, nearly significantly so for both genders, in Wave 11 than in Wave 9.[4] This difference should not be surprising, since in the last wave most of the adolescents have faces that approximate an adult's looks more closely.

[4]We cluster the standard errors of these fitted lines on child-mother pairs, given the appearances of most pairs in the sample in both Waves 9 and 11. Fitting the lines separately to observations in Waves 9 and 11 yields slopes of 0.208 (s.e. = 0.048) and 0.276 (s.e. = 0.066) for girls in the two waves, and 0.196 (s.e. = 0.040) and 0.265 (s.e. =0.060) for boys. Given that the slopes in the two waves do not differ statistically from each other, and that adding all the covariates reduces the differences still further, the body of the paper reports only the pooled regressions, clustering standard errors in each case on the pair.

The scatters and fitted lines in Figure 1 are based on the average ratings. As there are outliers, and to obviate issues of scaling, in much of the work we convert the beauty ratings into percentiles (ranging from the highest ranked, 100, to the lowest, nearly zero) to estimate (5). This rescaling has the virtue that the α^* are commensurable with easily usable estimates of the IIE, β_1. Other estimates use the average beauty ratings of child and mother rather than percentiles, which makes the estimated α more readily commensurable with estimates of β_2.

Columns (1) and (2) of Table 3 report the estimated impacts of the X and Z on B_t and B^M_{t-1} respectively (with estimates of the effects of the household's income/needs ratio and the site where the child was enrolled in the study not reported in the table), with percentiles of looks as the dependent variables. Mother's education is positively, but insignificantly associated with raters' perceptions of the child's looks, and positively and nearly significantly associated with her own looks; and Hispanic children are rated more highly than white non-Hispanic children. Overall, however, the covariates in X account for only a tiny fraction of the variance in the average ratings of the children's looks. Perceptions of mothers' looks are more strongly related to the mother's education than are their children's; but the largest impact on those ratings arises from differences in the mothers' ages: A two-standard deviation increase in age, 11 years, moves the rating of her looks down by a very significant 10 percentiles.

Columns (3)-(5) present estimates of Equation (5) for the entire pooled sample of Waves 9 and 11, and then separately by gender. The parameter α is tightly estimated around 0.2, and it differs very slightly by the gender of the child. Column (6) shows the estimates of (5) with average looks, rather than percentiles, used to measure the B^* (and using a first stage that is based on average looks). The estimate of α hardly differs between the two specifications.[5]

[5]Replacing percentiles and average beauty ratings by the logarithms of the average ratings also produces only minute differences in the estimated heritability of looks. Quadratic terms in the versions based on percentiles or on average looks ratings were small with t-statistics below 1.

C. Robustness Checks in the SECCYD

In the bivariate regressions based on the raw average ratings, Footnote 4 points out that α^* is greater when the sample is restricted to observations of B_t and B^M_{t-1} from Wave 11 than when both Waves 9 and 11 are included. That remains so if the sample underlying the estimates of (5) is restricted to Wave 11, with the estimated $\alpha^* = 0.219$ in Column (5) and 0.243 in Column (6); but the differences between estimates based on the full and restricted samples are small.[6]

With the significant positive impact of Hispanic faces on beauty ratings in the first stage, perhaps the results might change if the sample is restricted to white non-Hispanics. Re-estimating (5) on this reduced sample (N = 1,211), results tabled in the upper panel show that the estimates using percentiles of the distributions of looks are very similar to those shown in Table 3. This remains true when this sub-sample is broken down by gender.

A potential difficulty is that, as shown in Table 2, over 10 percent of raters considered the videos as too light. The middle panel of Table 4 presents estimates of (5) excluding those observations which were viewed by fewer than 80 percent of raters as having sufficient lighting. Again, the estimates of (5) differ only minutely from those shown in Table 3. Many videos were viewed by at least some raters as grainy. The bottom panel of Table 4 thus includes only those observations which a majority of raters viewed as not being grainy. Again, these estimates yield the same conclusions as the others.

D. Estimating Heritability Using Chinese Parents and Children

Missing information on father's looks, the estimates based on the SECCYD can only provide a lower bound on the parents' contribution to the child's looks. A glimpse at the size of ρ_{MF} and thus at the crucial parameter, α, is provided by information in the 2016 wave of the China Family Panel Studies

[6]With the child's and mother's beauty also rated when the child is 6 months old and in 3rd grade (roughly age 8), we can estimate the same equations as in the text. With the infants, the estimated $\alpha = 0.036$ (s.d. = 0.022); in 3rd grade, the estimated $\alpha = 0.112$ (s.d. = 0.027). The estimates of α thus increase steadily as the child moves from infancy through puberty. This is not surprising, since the child's face at age 15 is a pretty close approximation to her/his adult face, which is both more distinguishable from other faces. There is evidence that ratings of an adolescent's looks are highly correlated with ratings of her/his looks at middle age (Hatfield and Sprecher, 1986, p.283), so that the face that partly determines a person's income remains very similar over his/her labor-market experience.

(CFPS), used by, among others, Zhang *et al*., (2023). The studies contained information on married women's looks and those of their mothers and fathers in 96 families. Each person's looks were rated on a 7 to 1 scale by the interviewer at the end of a face-to-face interview.[7] Among the wives, whose average age was 33 (s.d. = 6.42), the average beauty rating was 6.22 (s.d. = 0.91) on this scale. Their mothers' looks ratings averaged 5.75 (s.d. = 1.22), their fathers' looks also averaged 5.75 (s.d. = 1.22). As in previous work on China using a sample from Shanghai in 1996 (Hamermesh *et al*., 2002), very few people are rated below average in looks.

The data set contains information on the region/municipality where the wife lives, whether her location is urban, her educational attainment, her number of children, and her age, which we use to form the vector X. Because the only wives included in this restricted sample are those living with their parents (quite unusual in China), we know that her parents live in the same area, so that Z contains the vector of regional indicators and the indicator of urbanicity. Because of the ordinal beauty rankings, we relate the wife's looks to the variables X using an ordered probit, then rank the residuals from that equation to get B^*_{t-1}, the percentile of the wife's looks after removing the covariate vector X. We obtain B^{*M}_{t-1} and B^{*F}_{t-1} similarly, using the covariates in Z in ordered probits, then ranking residuals. As in the previous sub-section, these covariates produce estimates of B^*, which allows estimating (3'). Only the number of children in the ordered probits on the wife's beauty, and the regional indicators in those describing the mother's and the fathers' looks, are statistically significant.

The first three columns of Table 5 present regressions of the relationship between the percentile of the ordered probit residuals of the wife's beauty on those of her mother and father. Both Columns (1) and (2) indicate large and statistically significant relationships between the wife's (residualized) beauty and those of her mother and father respectively. Including both parents' looks does not greatly increase the

[7]Rating at the end of the interview is standard in household surveys that include measures of beauty. One might be concerned that the ratings are contaminated by the interviewer-interviewee contacts. Evidence from the one survey that included interviewer ratings at the start and end of the contact shows that, although the average of ratings at the interviews end is higher than that at the start, they are very highly correlated (Hamermesh and Abrevaya, 2013).

implied estimate of 2α, which is 0.54. The reason is that the correlation of $B^{*F}{}_{t-1}$ and $B^{*M}{}_{t-1}$, ρ_{MF}, is 0.77 in this small sample. The final column in Table 5 presents estimates of the same model as in Column (3), but uses the raw ordered probit residuals rather than their percentiles. The estimates are very similar in the two columns.[8]

The difficulty in this sample is that the same interviewer rated the beauty of both the wife and her parents. To the extent that some interviewers are always relatively generous and others always relatively harsh in their ratings, the intergenerational correlations here will be positively biased. There is no way of adjusting for this difficulty in this dataset. For now, we use the estimates in Column (3), which imply that $\alpha = 0.27$ [= (0.415 + 0.129)/2]. We adjust this estimate to account for this measurement problem when we summarize the estimated values of α for use in our simulations of the extent to which beauty contributes to the intergenerational transmission of inequality.

IV. Heritability in Samples of Siblings

Our interest is in the heritability of beauty. Correlations of beauty among siblings, however, provide an additional avenue for measurement, since, like the genetic similarity between one parent and a child, the similarity of genes within a pair of siblings is also 0.5. In this Section we thus estimate α using samples of siblings; and as in Section III, we first use a large representative national survey, then a much smaller sample whose members arguably are able to do everything possible that they might wish to enhance their looks.

A. Beauty in the Add Health Survey

Because the Add Health survey was based on schools, there are substantial numbers of pairs of siblings at least 15 years old: 331 different brother pairs, 355 different sister pairs, and 525 different brother-sister pairs. Because most respondents were rated in more than one wave, the total number of usable observations over the four waves consists of 894 brother pairs, 1008 sister pairs, and 1384 brother-sister pairs. We exclude mono- and dizygotic twins and half-siblings from the estimating equations.

[8] Estimated the ordered probit using indicators of each parent's beauty rated 7, 6, or below, yields the same conclusions; the results do not stem from residualizing the tightly clustered ratings.

Table 6 presents contingency tables by type of sibling pair. Rows represent own beauty, and columns represent sibling's beauty. We combine ratings of 1 and 2 (very unattractive and unattractive) due to their small cell sizes. For all three types of pairs, brothers (panel A), sisters (panel B), and brother-sister pairs (panel C), a χ^2-test rejects the null hypothesis that own beauty and sibling beauty are independent at the 0.001 significance level. There is little deviation of an individual's own beauty from that of his/her sibling. For instance, based on panel A, the brother of a below-average-looking (1 or 2) male has a 58.1 percent chance of being average-looking (rating = 3) or below, and the brother of a very attractive male (rating = 5) has an 80.9 percent chance of being rated at least above average (4 or 5). Similar patterns also hold for sister-sister pairs. Among brother-sister pairs, the opposite-sex sibling of a below average-looking individual has a 64.9 percent chance of being average-looking or below, whereas the opposite-sex sibling of a very attractive individual has a 65.2 percent chance of being at least above-average. It is very unlikely that sibling pairs are on opposite ends of the beauty scale: The sibling of a very attractive individual has only a 2.7-3.5 percent chance of having below-average looks (Column 1, across three panels). Overall, the descriptive evidence suggests that beauty is strongly correlated between siblings, both within the same sex and across sexes.

B. Estimates of Heritability from Add Health

Table 7 reports estimates of α for pairs of siblings in the Add Health survey. The main results are presented in Columns (1)-(4), based on percentile ranks of beauty. The ranks are produced based on generalized residuals (or scores) from a series of ordered probit regressions over all Add Health respondents' beauty ratings by wave and gender on the covariates describing each sibling's age, race/ethnicity, father's and mother's absence from home, log household income at Wave I, and an indicator of missing values for household income. The only covariates that are usually statistically significant in these eight ordered probits are coming from a household with higher parental income (positive), being of Hispanic ethnicity (positive), and being African American (negative). Note that the estimated impacts of these last two variables are in the same direction as in the first-stage estimates based on the SECCYD.

Column (1) presents the results of relating the percentiles of residualized beauty based on all sibling pairs, while Columns (2)-(4) present the results for brother pairs, sister pairs, and brother-sister pairs respectively. The estimates of α range from 0.212 to 0.307, with the pooled estimate being 0.261. All the estimates are statistically significant at the 0.01 level.[9] Taken together, the estimates shown in Table 7 corroborate the results in Section III.[10]

The results are not an artifact of our estimation procedure or the adjustment for covariates. Column (5) lists further estimates, using the raw beauty indicators for each sibling and estimating ordered probits. In general, a one-category higher beauty rating of one sibling is associated with a significantly higher rating of the other sibling's beauty, with the exception of the move from the very sparsely populated "very unattractive" category to the "unattractive" category, which is not statistically significant at the 0.10 level.

Over the four waves the Add Health study also includes beauty ratings of 876 pairs of monozygotic twins, 1,317 pairs of dizygotic twins, and 887 pairs of half-siblings. Based on the estimate of α in Column (1) of Table 7, we should expect the estimated α to be 0.52 among pairs in the first group, 0.26 among those in the second group, and 0.13 among the half-siblings. Estimating the relationships between the residualized percentiles of beauty for each sibling in a pair in these samples, they estimates are 0.522 (s.e. = 0.033), 0.321 (s.e. = 0.029), and 0.196 (s.e. = 0.037) respectively. The estimate for pairs of monozygotic twins exactly equals that suggested by the estimate of α among pairs of full siblings. At 0.52, it illustrates that, while the siblings' genes are identical, the expressions of beauty are highly correlated, but by no means identical. The estimates for both dizygotic twins and half-siblings are slightly (but statistically significantly) higher than what the results among full siblings suggest.

The difficulty with these estimates is that in many of the pairs of siblings the same interviewer rated the beauty of each sibling. If, as has been observed in past studies in which interviewers rated the subjects'

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[9]Estimating the model separately for each wave of the survey, the estimated α = 0.342 (s.e. = 0.039), 0.378 (s.e. = 0.036), 0.209 (s.e. = 0.033), and 0.152 (s.e. = 0.033) in Waves I-IV respectively.

[10]As with the SECCYD data, we can restrict the sample to non-Hispanic whites and estimate the relationships between the siblings' (residualized) beauty over 1,839 pairs across the four waves of the survey. The estimate of α in this reduced sample is 0.252 (s.e. = 0.025), almost identical to that over the full sample which is 55 percent larger.

beauty, some interviewers are always more or less generous than others in their ratings, we will observe a positive bias to the inter-sibling correlation of beauty. To obviate this difficulty, we restrict the sample to the 1,310 (40 percent) pairs of observations in which the siblings were rated by different interviewers. The results of estimating the regression relating these siblings' (adjusted) looks are shown in the final column of Table 7. As expected, the relationship is much weaker, about half of that in the full sample, but still highly significant statistically.[11]

This redefinition of the sample generally requires that even the youngest siblings be living separately from each other. To the extent that living apart is self-selected, one might think that it is a choice made by those who are more different from their siblings along various dimensions, perhaps even in looks. If that is true, the estimate α = 0.125 is probably a lower-bound on the true α in this large sample of American siblings.

C. Estimating Heritability Using Billionaire Siblings

Hamermesh and Leigh (2022) had 16 students rate photographs of billionaires, each depicted alone, not in a group, in the Forbes tabulation of billionaires in 2008, using a scale from 10 (very beautiful) to 1 (not beautiful at all). The photographs were then randomized, entered five to a page into a PDF file, and shown to each rater. Each rater's scores were then unit-normalized, and the unit-normalized ratings of each observer were then averaged to obtain measures of beauty for 715 billionaires. As with the SECCYD data, we thus have many ratings of each sample participant's looks. Some of these people belong to the same clans, allowing the formation of 45 sibling pairs to estimate α.

Table 8 lists the estimates of the regressions of the standardized beauty of one person in the pair on the other's standardized beauty, with standard errors clustered on the clans. The first two columns are based on percentiles in the distributions of beauty among all 715 billionaires, the second two columns use the

[11]The estimates using samples of monozygotic twins (N=180), dizygotic twins (N=293, and half-siblings (N=285) who were evaluated by different interviewers were 0.225 (s.e.=0.066), 0.146 (s.e.=0.051), and 0.087 (s.e.=0.050) respectively. These estimated parameters are in roughly the same ratios to the estimate in Column 6 of Table 7 as are the estimates using the full samples.

average beauty rating of each member of the pair. Within each two columns, the first includes no covariates, the second includes an indicator of the gender of each person in the pair, the individuals' ages, and an indicator of Western origin. The standard errors are clustered on clans, of which 21 are represented among the 45 pairs of billionaires.[12]

The results differ somewhat depending upon whether beauty is measured in percentiles of the distributions of looks or by the average looks ratings. The reason is simply outlier bias in a small sample: One sibling pair contains a person whose rating is over two standard deviations above the mean while the other sibling's rating is below the mean. Using percentile ratings vitiates the importance of this extreme outlier pair. Even using the average ratings, however, when the covariates are included the estimated $\alpha = 0.219$. Taking that into the model of parents'/children's beauty, this estimate implies that two parents' beauty being one standard deviation above the mean would be reflected in a child's looks being 0.438 standard deviations above. Using percentiles produces a much larger estimate, $\alpha = 0.338$, above what is implied by any of the estimates of α in Section III and above that in the previous sub-section.

V. Calculating the Economic Impact of Heritable Beauty

We use the estimates of α from the four data sets in the previous two sections in conjunction with syntheses from the literatures estimating the impact of beauty on incomes and the intergenerational elasticity of income to measure the impact of heritable beauty.

A. A Synthesis on $\partial H_t/\partial H_{t-1}$

The evidence from the four samples is unsurprisingly not identical, but it does provide a reasonably narrow set of estimates of α, the relationship of expressed beauty between one parent and her/his child (or between siblings). These range from something greater than 0.105 in the SECCYD data; to 0.125 (the most conservative estimate in the Add Health data); to an adjusted 0.135 in the Chinese families (obtained by taking the estimated α and assuming that the issue of the same interviewer for all household members would

[12]One might argue that the measures of beauty used in the previous sub-sections depend upon people's ability—their incomes—to alter their looks by spending on beauty-enhancing items (although the evidence in Hamermesh *et al.*, 2002, suggests little alteration is possible. That argument seems even less relevant in this sample, since the billionaires surely have enough money to use whatever looks-enhancing technologies exist should they wish to do so.

yield the same ratio of adjustment as in the Add Health data); to 0.34 (in the data on billionaire siblings). In the calculations of (2') in the next sub-section, we therefore specify $0.30 \geq \alpha \geq 0.10$, so that $0.60 \geq 2\alpha = \partial H_t/\partial H_{t-1} \geq 0.20$, and we use 0.40 as the best estimate of this intergenerational correlation of parents' beauty and that of their child. It suggests that if both parents are in the top third of looks among Americans, their adult child will be at about the 64th percentile along this dimension.

B. Synthesizing the Literatures on Beauty and Intergenerational Inequality

As Equation (2') showed, in addition to the measure of the heritability of beauty, we also need estimates of the parameters β_1, the intergenerational income elasticity (or earnings), and β_2, the impact of beauty on income (earnings), to infer the total effect of inherited looks on a person's income (earnings). Each of these parameters has been estimated many times in the literatures, allowing obtaining the ranges in which they most likely lie and making producing new estimates nugatory. Since we showed in Section II that the impacts of parents' income and own beauty on income are independent, we can add the effects from the two literatures without worrying about any interactions.

We first infer a consensus about the magnitude of β_2. The difficulty is that all the estimates of this parameter, the effect of a one-unit increase in beauty, measure the impact of beauty on earnings, while most of the estimates of β_1, the IIE, look at income rather than earnings. Given the limitation on the estimates of β_2, we necessarily assume that whatever the literature on β_1 tells us about income applies equally to the intergenerational transmission of differences in earnings.

To bracket β_2 using studies based on percentiles of beauty, we measure the impact on log-earnings of a movement from the 16th to the 84th percentile of looks. Some studies offer direct estimates of the impact of a one standard-deviation increase in beauty on log-earnings, while others measure earnings, adjusted for covariates, at various percentiles of the distribution of looks. Hamermesh (2011, Chapter 3) summarized the results of 8 studies, inferring an impact of beauty (by percentile) on log-earnings of 14 log-points (0.14). Subsequent studies provide estimates ranging from 5 log-points in Australia (Borland and Leigh, 2014), to 6 log-points in the earnings as adults of a cohort of Wisconsin high-school graduates (Scholz and Sicinski, 2015), to 10 log points in a cohort of adult Kentucky college graduates (Stinebrickner *et al.*, 2019), to 12 log-points in a random national sample in the U.S. (Monk *et al*., 2021). Sierminska and Singhal (2023) summarize a number of recent studies other than these, with results suggesting an even larger effect. Given the estimates in the literature, we treat β_2 as ranging from 0.05 to 0.15, with the best estimate being 0.10, i.e., a two-standard deviation increase in beauty increases earnings by 10 log points.

Chetty and Hendren (2018, Figure 1) show that an increase of one rank of parents' income is associated with a 0.4 increase in the rank of an adult child's income. Corak (2013) calculates the intergenerational income elasticity of the United States as 0.47, while Justman and Stiassnie (2021, Figure 5) estimate an intergenerational elasticity of lifetime incomes for the youngest cohort in the PSID of 0.52, very similar to that for current incomes, 0.48, obtained by Aaronson and Mazumdar (2008). Lee and Solon (2009), using the PSID, conclude that the income elasticity averages 0.43. Among the two studies using earnings, Holmlund (2022), focusing on Sweden, finds an intergenerational elasticity of about 0.30, while Solon (2002) derives estimates ranging from 0.13 to 0.44 outside the U.S. It is difficult to pick single values out of this welter of estimates, but the best conclusion is that the true intergenerational earnings elasticity is 0.40 and ranges between 0.3 and 0.5.[13]

C. Putting the Estimates Together

Table 9 shows the overall impact of the two standard-deviation increase in parents' looks on the log-earnings of the child at various combinations of the parameters in (5). Taking the best estimate of β_2 from the literature and the best estimates from the analyses in Section IV yields a direct effect of a two standard-deviation difference in parents' beauty on an adult child's earnings of 4 log-points.[14] Using the

[13]We assume that all these estimates are of effects near the means. An increase in beauty among those with huge incomes (see Hamermesh and Leigh, 2022), will produce smaller effects on income (lower β_2) than the average. Similarly, people with substantial property income pass on more property to their offspring (Menchik, 1979), so that β_1 may be higher at the upper tail of parental income than at the average.

[14]While it does not get at the impact of the heritable characteristic beauty, the Add Health does allow direct estimation of Equation (1), since it includes parents' household income at Wave I, and the child's household income at Wave IV (ages 26-32) and the percentile of beauty (residualized from ordered probits that include the covariates that underlay the estimates in Table 7, excluding parents' household income). The adult child's age is held constant in estimating this version of (1), as are her/his parents' ages. The intergenerational income elasticity is estimated as 0.284 (s.e. = 0.013). The estimated intergenerational income elasticity is slightly smaller than that found in most of the literature, perhaps because the two generations' incomes are observed at different ages. Based on the percentiles, $\beta_2 = 0.00343$

best estimates of β_1 and β_2 from the literature gives an indirect effect of 4 log-points of earnings. Thus the best estimate of the total effect of this inherited trait, through the child's beauty directly and indirectly through the transmission of other income-producing characteristics, is 8 log-points of earnings (the middle row of the middle column in Table 8). The direct effect on earnings, however, could be as small as 1 log-point or as large as 9 log-points. The total effect could be as small as 2.5 log-points or as large as 16.5 log-points. The central conclusion, however, is that this demonstrably heritable trait raises offspring's incomes. It does so both through the inheritance of the income-increasing trait and through its impact on the inequality of parents' incomes that is transmitted to their children.

Taking the best estimate of the total impact of parents' beauty on their adult children's earnings, 8 log-points, is this impact small or large? Among all those respondents in the CPS Outgoing Rotation Groups of 2022 who usually worked at least one hour per week and whose reported usual weekly earnings divided by their reported weekly workhours at least equaled the U.S. minimum wage, the standard deviation of log-earnings was 0.71. Among those who usually worked at least 35 hours/week, it was 0.44. Comparing even the higher figure to the best estimate of the impact of parents' looks, 0.08, suggests that a two standard-deviation difference in parents' beauty raises their adult child's earnings by 0.113 standard deviations (or 0.056 standard deviations of earnings per standard deviation of parents' looks).

Basing comparisons on to other work on the usual one standard-deviation increase (here, in both parents' beauty), an impact of 0.056 (-0.113/2) standard deviations does not appear large. Remember, however, that with the assumption of an intergenerational income elasticity of 0.4, this effect is 14 percent of the effect summarized through the transmission of income inequality. In monetary terms, compared to average earnings of all workers in the U.S. in 2022, it amounts to over \$2300 per annum, or an extra \$106,000 of income over an average working life of 45 years. By these criteria, the estimate implies a

(s.e. = 0.00029); so that a two standard-deviation change in B* implies an increase in child's income of 23 log-points, at the high end of the literature estimating the direct economic impact of beauty.

substantial impact. Also, compared to estimates of the impacts of shocks in a variety of other areas, it is not tiny.[15]

VI. Conclusions and Other Applications

A trait which increases earnings and that we now know is demonstrably heritable raises one's offspring's earnings through two mechanisms: 1) Its expression in the child's characteristics—a direct effect; and 2) The transmission to the next generation of the increase in parents' incomes that it produced. To estimate the magnitude of the effects, we take the example of beauty (looks, appearance). Using four datasets, two that allow relating parent(s') looks to those of their children, two that enable measuring the correlation of siblings looks, we estimate that, if parents' looks are ten percentage-points above average, their child's looks will be four percentage-points above average. Combining this with estimates from the literature on the effects of beauty on earnings, and with measures of the intergenerational elasticity of income (or earnings), simulations suggest that the best estimate is that a one standard-deviation increase in parents' looks raises their child's adult earnings by 0.05 standard deviations.

Differences in beauty are just one cause of inequality among adults that arise from partly heritable physical traits. Biologists have now demonstrated that height is linked to specific genes (Wood *et al*., 2014; Tyrrell *et al*., 2016); and a substantial literature has demonstrated the role of height on earnings (e.g., Schultz, 2002; Persico *et al*., 2004). Similarly, adult differences in weight have now been shown to be partly genetically determined (McPherson, 2007; Tyrrell *et al*., 2016); and economists have examined the impact of obesity/weight on earnings (Cawley, 2015, summarizes this literature). Yet another example is the partially genetic determination of the intergenerational transmission of education and skill (e.g., Rietveld *et al*., 2013; and see the economic modeling of this phenomenon by Rustichini *et al*., 2024).[16] The impacts

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[15]For examples, the effect of an agricultural plague on men's height in France in the late 19th century was 0.03 standard deviations of height (calculated from Banerjee *et al*., 2010, Table 1). The impact on adult earnings of having a teacher whose value-added is one standard deviation above the mean raises adult earnings by 1.65 percent of mean earnings (Chetty *et al*., 2014, p. 2654). Applying this estimate to the CPS-ORG data discussed in the text implies an increase of 0.03 standard deviations of adult earnings.

[16]There is now some evidence that particular genes are linked to differences in measures of intelligence, although the links appear to be much more complex than those to height or weight, or even to beauty. (See the excellent review and

of each of these traits on the intergenerational transmission of inequality could be studied using the method employed here.

A related thread of the literature on contemporary income inequality has linked it to intergenerational income mobility (Corak, 2013; Adermon *et al*., 2021), showing a positive correlation across countries in the two sets of outcomes and offering explanations, but not yet any economic theory, underlying it. The role of heritable physical traits in linking these two phenomena should be explored. This might put some empirical meat directly on the bones of the theory described by Becker and Tomes (1979).

discussion by Nisbett *et al*., 2012.) One could wade into the long-standing debate on nature vs. nurture in intelligence (e.g., Kamin, 1974; Herrnstein and Murray, 1994) if one had acceptable tests of intelligence as measured in adult-child pairs. On this topic, however, the Dantean admonition, "*Lasciate ogni speranza, voi ch'entrate*," seems relevant.

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Table 1. Estimates of (1), Men, Wisconsin Longitudinal Study, and National Longitudinal Study of Adolescent to Adult Health

Dep. Var.: ln(Own household income)[a]	**WLS**			**Add Health**		
	Mean (s.d.)	Parameters		Mean (s.d.)	Parameters	
	\$71,092 (\$58,123)			\$69,106 (\$42,412)		
Ind. Vars.:						
ln(Parents' household income)[b]	\$6,470	0.270	0.265	\$55,244	0.234	0.226
	(\$7,777)	(0.081)	(0.081)	(\$53,632)	(0.017)	(0.017)
Attractive[c]	0.339		-0.122	0.480		0.124
			(0.125)			(0.020)
Unattractive[c]	0.156		-0.445	0.065		-0.130
			(0.163)			(0.049)
Adj. R^2		0.0036	0.0055		0.0480	0.0573
N	2,844	2,844	2,844	6,067	6,067	6,067

[a]WLS: yearly own total household income, 1992-93, mid-50s *rphef*

[a]Add Health: yearly own total household income, 2007, 26-32, *h4ec1*

[b]WLS: yearly parental total household income, 1966, *pi5760*

[b]Add Health: yearly parental total household income, 1994, *pa55*

[c]WLS: top 1/3 of beauty, 1957, *meanrat*

[c]Add Health: rating of 4 or 5, 2008-09, *h4ir1*

[d]WLS: bottom 1/6 of beauty, 1957 , *meanrat*

[d]Add Health: rating of 1 or 2, 2008-09, *h4ir1*

Table 2. Descriptive Statistics of the SECCYD Sample, Waves 9 and 11*

Variable:	All	Boys	Girls
Child's looks--average	2.980	2.854	3.099
	(0.611)	(0.565)	(0.629)
Mother's looks--average	2.807	2.814	2.800
	(0.572)	(0.580)	(0.564)
Child's looks—std. dev. of ratings	0.754	0.748	0.759
	(0.155)	(0.164)	(0.145)
Mother's looks–std. dev. of ratings	0.747	0.752	0.741
	(0.176)	(0.182)	(0.170)
Video sufficiently light	0.885	0.889	0.881
Video grainy	0.560	0.565	0.556
Mother's age	29.54	29.20	29.87
	(5.19)	(5.43)	(4.94)
Mom education:			
High school	0.178	0.197	0.159
Some college	0.323	0.304	0.341
College or college plus	0.449	0.435	0.463
Black	0.063	0.074	0.053
Hispanic	0.058	0.070	0.047
N =	1378	674	704

*Standard deviations in parentheses. Observations with 10+ ratings of both child and mother.

Table 3. Estimates of First-Stage Equations and (5), Estimates of Impacts on Child's Beauty, N = 1,378[a]

Dep. Var.:	Percentile Rank					Average Rating
	First Stage		(5)			(5)
	Child Beauty	Mother's Beauty	All	Girls	Boys	All
Ind. Var.						
B^{*Mom}	------	-------	0.214	0.207	0.221	0.221
			(0.030)	(0.041)	(0.043)	(0.033)
Black	-3.839	-1.213				
	(3.352)	(3.387)				
Hispanic	9.175	3.615				
	(3.526)	(3.970)				
Mother's Education:						
High school	2.913	0.271				
	(4.584)	(4.723)				
Some college	5.182	8.053				
	(4.431)	(4.691)				
College or more	4.867	7.351				
	(4.536)	(4.823)				
Mother's age	-------	-1.450				
		(0.199)				
Adj. R^2	0.031	0.104	0.041	0.039	0.044	0.039
N =	1,378	1,378	1,378	704	674	1,378

[a]Standard errors in parentheses clustered on children-mother pairs. Also included in the first stage are indicators of the site where the child was enrolled in the study and the quartile of the income/needs ratio.

Table 4. Miscellaneous Specifications Estimates of (5) over Different Samples, Dep. Var.=B^{*a}

Ind. Var.	All	Girls	Boys
		Non-Hispanic Whites	
B^{*M}	0.208	0.197	0.221
	(0.032)	(0.044)	(0.047)
Adj. R^2	0.039	0.035	0.042
N =	1,211	634	577
		With Good Video Lighting[b]	
B^{*M}	0.210	0.205	0.217
	(0.033)	(0.048)	(0.046)
Adj. R^2	0.039	0.037	0.042
N =	1,164	569	595
		With Video Not Grainy[c]	
B^{*M}	0.258	0.233	0.283
	(0.043)	(0.061)	(0.063)
Adj. R^2	0.056	0.045	0.040
N =	618	305	313

[a]Standard errors in parentheses.

[b]At least 80 percent of rates state the video is sufficiently light.

[c]At least 50 percent of raters state the video is not grainy.

Table 5. Estimates of (5) Based on the China Family Panel Study, Dep. Var. B^* (N = 96)[a]

Based on:	**Percentile Rank of Ordered Probit Residual**			**Ordered Probit Residual**
B^{*M}	0.515	------	0.415	0.334
	(0.088)		(0.140)	(0.095)
B^{*F}	------	0.450	0.129	0.159
		(0.092)	(0.140)	(0.090)
Adj. R^2	0.257	0.194	0.256	0.326

[a]Standard errors in parentheses. Covariates used to generate B^* include vectors of wife's region, urban status, year of age, years of schooling, number of children, and health; parents' equations include vectors of region and urban status. The region and urban status are used to create the B^*_{t-1} of the mother and father.

Table 6. Distributions of Beauty Ratings within Sibling Pairs, by Type of Pair, Add Health 1994-2008.

	(1) Row %	(2) Row %	(3) Row %	(4) Row %	
A: Brother Pairs					
Sibling Beauty:	1 or 2	3	4	5	N
Own Beauty:					
1 or 2	22.6	35.5	22.6	19.4	62
3	6.3	59.9	28.0	5.8	446
4	3.7	42.1	44.3	9.9	323
5	3.2	15.9	46.0	34.9	63
Column %	6.3	48.7	34.8	10.3	
N =	56	435	311	92	894
	$\chi^2 = 131.07$; $p < 0.001$				
B: Sister Pairs					
Sibling Beauty:	1 or 2	3	4	5	
Own Beauty:					
1 or 2	24.0	36.0	30.0	10.0	50
3	5.4	53.0	32.2	9.4	404
4	2.9	34.4	48.5	14.1	410
5	3.5	24.3	32.6	39.6	144
Column %	5.1	40.5	38.8	15.7	
N =	51	408	391	158	1008
	$\chi^2 = 150.13$; $p <0.001$				
C: Brother-sister pairs					
Sibling Beauty	1 or 2	3	4	5	
Own Beauty:					
1 or 2	10.4	54.5	26.0	9.1	77
3	9.2	52.8	32.4	5.7	612
4	5.5	41.5	41.1	11.8	508
5	2.7	32.1	39.0	26.2	187
Column %	7.0	45.9	36.1	10.9	
N =	97	636	500	151	1384
	$\chi^2 = 93.72$; $p < 0.001$				

Note: Row percentages. χ^2 tests the null hypothesis that the rows and columns are independent.

Table 7. Estimates of α Based on Sibling Pairs, Add Health 1994-2008.

Dep. Var.:	**Percentile Rank**				**Raw Rating**	**Percentile Rank**
	All	Brothers	Sisters	Brother-sisters	All	Different Raters
B^{*sib}	0.261	0.288	0.307	0.212		0.125
	(0.019)	(0.037)	(0.033)	(0.029)		(0.028)
Sib: very attractive					0.705	
					(0.079)	
Sib: attractive					0.329	
					(0.044)	
Sib: unattractive					-0.326	
					(0.090)	
Sib: very unattractive					-0.206	
					(0.225)	
Adj. R^2 or pseudo-R^2	0.069	0.083	0.094	0.047	0.031	0.015
N different pairs	1,211	331	355	525	1,211	887
N pairs	3,286	894	1,008	1,384	3,286	1,310

Note: Standard errors in parentheses are clustered at the family level. Columns (1)-(4) and (6) are results based on the percentile ranks of the residuals from ordered probits estimated over all sample members, not only siblings, separately by gender at each of the four waves. The covariates include age, race/ethnicity, father's and mother's absence from home, log household income at Wave I, and an indicator of missing values in household income as explanatory variables. Column (5) reports the coefficients from an ordered probit regression on the raw beauty ratings, controlling for the covariates listed above.

Table 8. Estimates Based on Sibling Pairs Among Billionaires, 2008, N Pairs=45, N Clans=21 (Dep. Var. = B_1)[a]

Dep. Var.:	Percentile Rank		Average Rating	
Ind. Var.:				
B_2	0.447 (0.183)	0.338 (0.104)	0.278 (0.145)	0.219 (0.076)
Adj. R^2	0.177	0.543	0.107	0.515
Covariates	No	Yes	No	Yes

[a]Standard errors in parentheses, clustered on clans. The covariates are the gender of each person in the pair and their ages, and whether the pair is of Western origin.

Table 9. The Intergenerational Impact of Beauty on Earnings (Change in log-Points in Response to a Two-Standard Deviation Increase in Beauty in Generation t-1)

$\partial H_t/\partial H_{t-1} = 0.20$

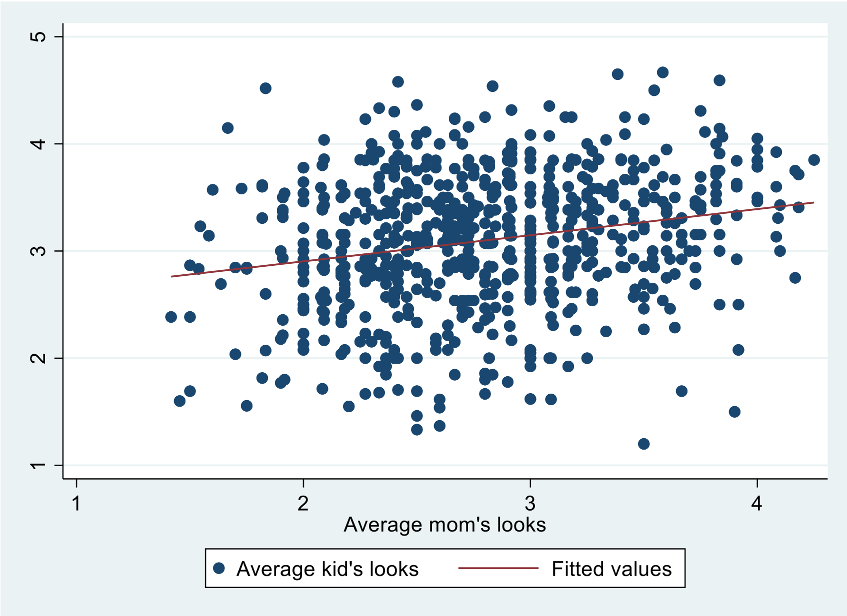
		$\beta_2 =$		
		0.05	**0.10**	**0.15**
Direct Effect:		0.010	0.020	0.030
Total Effect:				
	0.30	0.025	0.050	0.075
β_1=	**0.40**	0.030	0.060	0.090
	0.50	0.035	0.070	0.105

$\partial H_t/\partial H_{t-1} = 0.40$

		$\beta_2 =$		
		0.05	**0.10**	**0.15**
Direct Effect:		0.020	0.040	0.060
Total Effect:				
	0.30	0.035	0.070	0.105
β_1=	**0.40**	0.040	**0.080**	0.120
	0.50	0.045	0.090	0.135

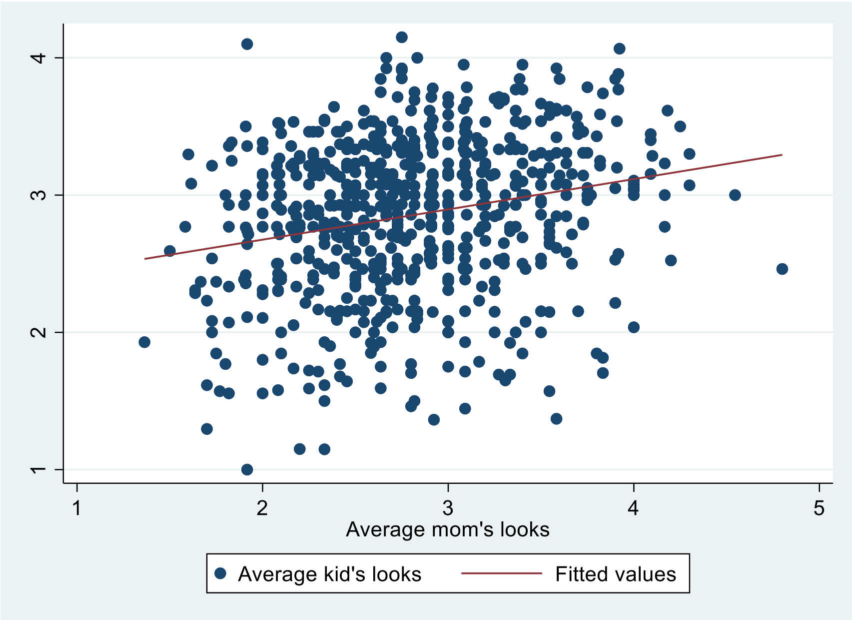
$\partial H_t/\partial H_{t-1} = 0.60$

		$\beta_2 =$		
		0.05	**0.10**	**0.15**
Direct Effect:		0.030	0.060	0.090
Total Effect:				
	0.30	0.045	0.090	0.135
β_1=	**0.40**	0.050	0.100	0.150
	0.50	0.055	0.110	0.165



LooksChild = 2.416 + 0.244LooksMother; Adj. $R^2 = 0.047$
(0.135) (0.046)

Figure 1a. Relation of Child's Average Looks Rating to Mother's, Girls, SECCYD Waves 9 and 11



LooksChild = 2.234 + 0.221LooksMother; Adj. $R^2 = 0.050$
(0.115) (0.040)

Figure 1b. Relation of Child's Average Looks Rating to Mother's, Boys, SECCYD Waves 9 and 11