Labour Economics 76 (2022) 102153

Contents lists available at ScienceDirect

Labour Economics

journal homepage: www.elsevier.com/locate/labeco

"Beauty too rich for use": Billionaires' assets and attractiveness☆

Daniel S. Hamermesh*, Andrew K. Leigh**

333 West 57th Street, New York, NY 10019, United States

A R T I C L E I N F O

Keywords:
Financial wealth
Education
Sample truncation

A B S T R A C T

We examine how the net worth of billionaires relates to their looks, as rated by 16 people of different gender and ethnicity. As a group, billionaires are both more educated and better-looking than average for their age. However, when we compare among billionaires, wealth is neither related to beauty. nor to educational attainment. The results do not arise from measurement error or nonrandom sample selectivity. They are consistent with econometric theory about the impact of truncating a sample to include observations only from an extreme tail of the dependent variable. The point is underscored by comparing estimates of earnings equations using all employees in the American Community Survey to those using a sample of just the top 0.1 percent of earners. The findings suggest the powerful role of luck within the extremes of the distributions of economic outcomes. That empirical regularities tend to disappear in the far tails is relevant to analyzing any sample of highly successful or unsuccessful individuals.

1. Motivation

An immense literature has examined the effects of beauty on labor-market outcomes and economic success more generally (summarized in Hamermesh, 2011). This literature is still burgeoning, as shown by recent research on beauty and labor markets for the U.S. (Scholz and Sicinski, 2015; Monk et al., 2021), for Australia (Borland and Leigh, 2014), and for many other countries (Sierminska, 2015). Our question is whether these now very well-established findings also characterize the economic well-being of the most economically successful people on the planet—billionaires.

To answer this question, in Section II we describe the sample of plutocrats, including explaining how we evaluated their attractiveness. Section III presents the analysis of the data that were developed, focusing on the relationship between the billionaires' assets and their rated beauty and educational attainment, and controlling for other objective characteristics that might affect differences in net financial worth. In Section IV we present reasons explaining our results and offer another example, using the 2018 American Community Survey, that helps to rationalize the findings about billionaires and that illustrates a general econometric point.

In a nutshell, our results show that a sample that is taken from the extreme tail of the dependent variable no longer exhibits the systematic patterns seen across the distribution. Billionaires are better-educated and better-looking than the general public. But among billionaires, attractiveness does not predict wealth. This finding has important implications for any empirical study where the sample is highly selected. Empirical regularities that are common in the general population may not hold up among atypical subsets of the population, whether drawn from the elite (e.g., Olympic athletes, Fortune 500 CEOs) or the most disadvantaged (e.g., prisoners, the homeless). Within these groups, outcomes are more likely to be due to unobservables and pure chance than observable traits.

2. The sample of billionaires

Since 1987, the U.S. business magazine *Forbes* has compiled a list of the world's billionaires. The data have rarely been used by economists, with Castaldi and Milaković (2007), Kaplan and Rauh (2013), and Bagchi and Svejnar (2015) being the few examples of studies using these data; and none appears to have employed this source of data to analyze how the billionaires' personal characteristics determine their wealth.

Estimating billionaires' wealth involves dozens of reporters across multiple countries. *Forbes* aims to calculate net worth, including public and private firms, real estate, and other assets, minus any debts (Dolan, 2012). The value of private companies is calculated by combining estimates of revenues or profits with price-to-revenue or price-to-

☆ Romeo and Juliet, Act. I, Scene 5.

* Corresponding author.
E-mail address: hamermes@eco.utexas.edu (D.S. Hamermesh).

** Sue Killam Professor Emeritus, University of Texas at Austin, Research Fellow, IZA, and Associate, NBER; Parliament of Australia, and Research Fellow, IZA.
The authors thank Jesper Roine and Daniel Waldenström for sharing their *Forbes* wealth spreadsheet, Andrew Hussey, Todd Jones, Matthias Krapf, Jungmin Lee, Younghoon Lee, Paul Menchik, Junsen Zhang, participants in seminars at several universities, two anonymous referees and the Co-editor for helpful comments, and Susanne Schmidt for outstanding research assistance.

https://doi.org/10.1016/j.labeco.2022.102153
Received 9 November 2021; Received in revised form 9 February 2022; Accepted 21 March 2022
Available online 23 March 2022

Table 1
Descriptive statistics of the sample of billionaires and their looks (N = 715).

Variable	Mean Std. dev.	Range
Net worth (in 2021 billion USD)	$5.58 ($7.89)	[$1.24, $76.88]
Age	61.2 (13.8)	[23, 99]
Male	0.924	
Western	0.766	
College graduate	0.730	
Inherited	0.283	
Beauty ratings:		
Raw:	4.78 (1.81)	[1, 10]
Ranges: Min., Max.	[-0.58, 1.33]	[-2.65, 4.06]
Standardized:		
Mean, std. dev., range: Average 16 ratings	0.01 (0.57)	[-1.24, 2.27]
Average 8 male raters	0.01 (0.60)	[-1.19, 2.42]
Average 8 female raters	0.00 (0.66)	[-1.51 2.52]
Average 16 raters, rater/billionaire match by gender, ethnicity	0.01 (0.73)	[-1.54, 2.94]

earnings ratios for similar public firms. Families are excluded if wealth per family member is below one billion U.S. dollars. *Forbes* attempts to verify its estimates with the billionaires themselves, although some do not respond. Royal families and dictators, whose wealth is contingent on their position, are not included in the billionaire list (Kroll, 2006). Our data are from the 2008 list, which used as its "counting day" February 11, 2008 (Kroll, 2008), and which estimated the wealth of 1125 billionaires, publishing photographs of 727.[1]

We include in Table 1 and in the subsequent analyses only the 715 billionaires (of the 727 with pictures) who were photographed alone and on whom we could obtain information on education.[2] To update the data, all monetary values were inflated to 2021 U.S. dollars. The first row in the upper panel of Table 1 describes these individuals' net financial worth. Unsurprisingly, the distribution is quite skewed, with the standard deviation exceeding the mean and, as in most such distributions, with a long right tail.[3]

The billionaires averaged age 61, with substantial variation around that (ranging from Mark Zuckerberg, *Facebook*, age 23, to John Simplot, potato processing, age 99). Ninety-two percent of the billionaires on the list were men. We classified them by their country of residence, creating the variable Western for all those based in North America, Europe (including Russia), Israel, South America, Australia, and New Zealand. Billionaires who reside in China, Egypt, Hong Kong, India, Indonesia, Japan, Malaysia, Nigeria, Oman, the Philippines, Saudi Arabia, Singapore, South Africa, South Korea, Taiwan, Turkey, or the United Arab Emirates were considered non-Western. Seventy-seven percent were coded as Western. We obtained billionaires' educational attainment, creating an indicator of whether they were college graduates. A remarkable 73 percent had attained at least a four-year college degree. We also coded an indicator *Inherited* for billionaires who had inherited their businesses, although in many cases the business had been greatly expanded by the inheritors. These heirs accounted for 28 percent of the usable sample.

We use a panel of 16 students at the Australian National University, aged in their twenties and thirties, of whom eight were men and eight women, to rate the beauty of each billionaire. Two of the male raters and one of the female raters had non-Western surnames. Billionaires' photographs were taken from the *Forbes* website, and placed in random order into a PDF document, with five photographs appearing on each page.[4] The document contained fields that allowed raters to enter their scores, so the ratings were done on-screen rather than in print. Each rater was paid A$40 (US$29) to rate the photographs. As we detail below, the coherence among the views of the raters in this study accords with other studies of beauty and economic outcomes, and robustness checks suggest that our findings are not driven by atypical imprecision in the measurement of attractiveness.[5] Indeed, as in Hamermesh and Abrevaya (2013), our results do not change qualitatively if we use randomly selected halves of the set of 16 raters.

Raters were asked to assign each billionaire a score between 1 and 10, with 1 being "very beautiful," and 10 being "not beautiful at all." Although this scale is the reverse of what is often used, we are not worried that the raters misinterpreted it: The scale appeared at the top of every page of the rating document, and there was a high positive correlation across rater-pairs. (All except one of the 120 rater-pair correlations were statistically significant at the 1 percent level, with the remaining one significant at the 5 percent level). For ease of interpretation, in what follows we reverse the scale so that it takes the conventional form, with the highest rating, 10, reflecting the greatest attractiveness.

If the raters had graded the beauty of the billionaires symmetrically, their scores would have averaged 5.5 (the midpoint of the 10 to 1 scale). Instead, the average across all ratings and raters was 4.78. As Fig. 1, a

[1] In broad terms, the methodology for compiling the *Forbes* global billionaire list appears to follow the approach that *Forbes* uses to estimate the wealth of the most affluent 400 people in the United States, so we may draw some conclusions on data accuracy from the more frequent academic studies that have used the *Forbes* 400 dataset. Anecdotally, that dataset is clearly imperfect. Donald Trump exaggerated his wealth to gain a place on the list, while the three principals of Twitter did not make the billionaires' list until their initial public offering in 2013. Estimating the accuracy of the *Forbes* 400 list, Saez and Zucman (2016) find that reported individual net worth is consistent with confidential tax return data from the IRS. Similarly, Moretti and Wilson (2022) find that state estate tax revenues increase as expected when someone on the *Forbes* 400 list dies in that state. Raub et al. (2010) match individual estate tax data to deceased individuals in the *Forbes* 400 and report a high correspondence for asset classes that have a clear market value (such as stocks and bonds), but a greater disparity for debt and assets whose value is more subjective (although it is unclear to what extent the disparity reflects overestimation by *Forbes* researchers, or tax avoidance/evasion by those on the list). Finally, investigating the quality of the *Forbes* global billionaire list, Freund and Oliver (2016) conclude that that dataset is most likely to omit or underestimate wealth for billionaires whose assets are diversified, and those whose wealth is held in a private company.

[2] We could not obtain the educational attainment of five of the 727; and seven others were only photographed with one or more other people.

[3] The wealthiest three billionaires in 2008 were Warren Buffett, Carlos Slim Helu, and Bill Gates.

[4] Most photographs appear to be taken by news photographers at public events. Most images show only the billionaire's face, although some include their torso, and a few include the entire body. Because many of the photographs are not taken front-on, it would be impractical to use facial symmetry software to analyze the images.

[5] Babin et al. (2020) explore various other approaches to measuring beauty, including an incentivized coordination game (in which raters are paid a premium if their score matches the modal score from other raters). They find that different metrics have little impact on the beauty ratings: among their standardized measures of attractiveness, Cronbach's alpha is 0.93. This suggests that our (null) results would be unlikely to differ had we chosen another measure of attractiveness.

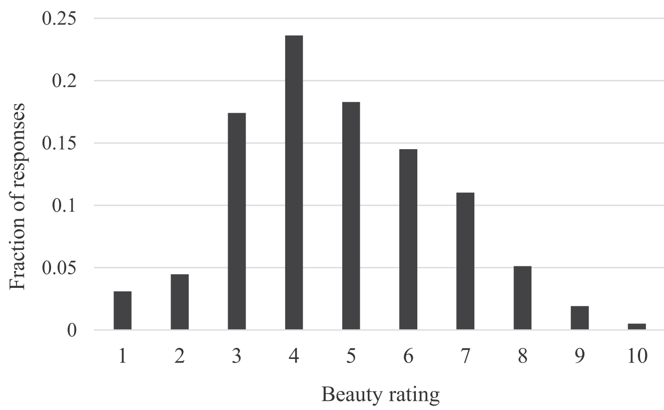

Fig. 1. Histogram of 11,438 beauty ratings.

histogram of the 11,438 individual ratings, shows, the distribution is shifted leftward from what symmetry would suggest.[6] Each of the three lowest ratings appears over twice as frequently as its counterpart at the higher end of the beauty ratings. That the typical rater found the attractiveness of the typical billionaire to be below average is unsurprising: We know that even if raters are instructed to abstract from the effects of age on appearance, they are incapable of doing so. The looks of older people are generally rated low (Hamermesh, 2011, Chapter 2), and the billionaires, average age 61, do not differ from others in this regard. To circumvent this problem and to account for heterogeneity in raters' evaluations, we unit-normalize each rater's evaluations.

As the bottom panel of Table 1 shows, there was substantial heterogeneity in how the 16 raters perceived the looks of the subjects. The lowest-variance rater included a standardized range of less than two standard deviations, while at the other extreme a rater included a range of over six standard deviations.[7] Given the idiosyncrasies inherent in the ratings, for each billionaire we first took a simple average of all 16 standardized ratings, with statistics describing this aggregation reported in the third row of the bottom panel of Table 1. [8]

Because the raters assessed beauty somewhat similarly, the standard deviation of the average of the 16 standardized ratings is below one (as it is in Biddle and Hamermesh, 1998, which used a similar rating scheme). The Cronbach alpha for the 16 raters is 0.88, suggesting substantial agreement among raters, as did the pairwise correlations. The next two rows aggregate the ratings by male, then by female raters.[9] There is somewhat more variation in the women's ratings of the billionaires, but the ranges and the variability of the ratings are quite close by gender of the raters.

The final row of the table presents statistics describing an aggregation of ratings based on matches of the location and gender of the billionaires to the ethnicity and gender of the raters. Thus, the average rating assigned to the 506 Western males was the average standardized rating by the six ethnically Western male students, that assigned to the 14 non-Western females was the rating by the non-Western female student, etc. Perhaps because those who are ethnically similar and of the same gender may be better able to distinguish differences in attractiveness, these ratings exhibit greater variability and a wider range.[10]

The average standardized rating of the attractiveness of the 54 female billionaires in the sample is one standard deviation above that of men's, a difference seen in some but not all studies.[11] The correlation of billionaires' ages and their average standardized beauty rating is -0.44, and the average beauty rating drops more rapidly with age among women billionaires, exactly as it does generally (Hamermesh, 2011). There is no difference in average ratings within male or female billionaires between those who did and did not inherit their wealth.

3. The impact of looks on assets

We relate the billionaires' assets (in logarithms) to various indexes of their beauty, as assessed by the entire panel of raters. Column (1) of Table 2 presents the simple bivariate relationship between the two. The point estimate is small, statistically insignificant, and negative—there is no evidence of the positive relationship between economic outcomes and looks that has been so widely demonstrated in the literature. Note that although it is likely that everyone in the sample has the means to invest in improving her/his looks, a positive correlation between wealth and such investment would generate a positive bias in the relationship between attractiveness and wealth.

Column (2) adds all the available controls to the equation. The effect of beauty remains small and statistically insignificant.[12] The impact of having attained a college degree on net financial worth within the sample is also essentially zero: Additional education, defined as having completed college, has a small negative but statistically insignificant effect.

Billionaires based in Western countries are 27 percent wealthier than otherwise identical billionaires. Male billionaires are 14 percent wealthier than female billionaires, once we account for gender differences in inheritance status (since 23 percent of male billionaires, but 87 percent of females in the sample inherited substantial wealth). There is a U-shaped relationship between wealth and age, with a minimum at age 56 (the 35th percentile of the age distribution). The marginal effect of age becomes positive with a t-statistic above one after age 66 (the 63rd percentile of age). Presumably the youngest billionaires are very successful *nouveaux ultra-riches*, whereas after age 56 much of the increase reflects accumulation based on existing wealth.

Having inherited at least part of a business places a billionaire's wealth 22 percent above that of another billionaire who did not inherit. This inference does not imply that financial inheritance is the only advantage that enabled these people to become billionaires: Luck and social connections may matter too. It simply suggests that having received large financial transfers from one's parents, late spouse, or siblings tends to move one up the billionaire list.

[6] The total number of ratings included is short by 2, because each of two raters failed to assess the looks of one billionaire.

[7] We recognize that this suggests that unit normalization does not perfectly describe each discrete set of ratings. Using other summary measures of the ratings did not qualitatively alter the results reported in the next section.

[8] The means here and below differ very slightly from zero because the underlying ratings were of all 727 billionaires rather than the 715 included in the sample for which the statistics in Table 1 are presented and which underlies our analyses.

[9] The statistics reported describe the distributions of these averages. Their range is greater than that of the distribution of all 16 averages because extreme ratings are smoothed out more when all 16 ratings are averaged.

[10] This has been shown repeatedly, with a clever experiment (Kamakura and Jones, 2014) demonstrating it most clearly.

[11] While the women are slightly younger than the men (age 59 versus 61), even accounting for the slight age difference they are rated as substantially more attractive than the male billionaires.

[12] It is not straightforward to compare our results with those in the literature, since many previous estimates are based on whether a person is rated as above or below average attractiveness, rather than on standard deviations of the beauty distribution (as we do). If, however, we assume that above-average and below-average beauty each denote approximately a 1.5 standard deviation shift along the distribution (i.e., a move from the 13th to 50th percentile, or from the 50th to 87th percentile), then the significant results reviewed in Liu and Sierminska (2014) suggest that a one standard deviation increase in beauty is associated with a 3 to 13 percent increase in earnings. By contrast, our estimates in columns (1) and (2) of Table 2 suggest that the 95 percent confidence interval on the impact of beauty on wealth among billionaires ranges from -13 percent to +9 percent without controls, and from -16 percent to +10 percent with controls. The comparisons suggest that our estimates are well below those found in the literature.

Table 2
The relationship between wealth and beauty among billionaires*.

	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Ind. Var.:	Entire Sample				Men		
Beauty (average of 16 standardized ratings)	-0.021(0.054)	-0.030(0.065)	——	——	0.014 (0.071)	——	——
Beauty (raters matched by ethnicity & gender)	——	——	0.033(0.042)	0.065(0.051)	——	0.092(0.055)	0.082(0.062)
Age	——	-0.016(0.017)	——	-0.012(0.017)	-0.020(0.018)	-0.016(0.018)	-0.032(0.021)
Age^2	——	0.00014(0.00014)	——	0.00013(0.00014)	0.00018(0.00015)	0.00016(0.00015)	0.00030(0.00017)
Western	——	0.239(0.076)	——	0.209(0.075)	0.187(0.079)	0.162(0.077)	0.248(0.089)
Male	——	0.129(0.132)	——	0.040(0.126)	——	——	——
College grad	——	-0.028(0.072)	——	-0.040(0.071)	-0.035(0.075)	-0.045(0.074)	-0.054(0.081)
Inherited	——	0.200(0.074)	——	0.197(0.074)	0.193(0.075)	0.192(0.075)	——
Adj. R^2	-0.001	0.019	-0.0006	0.021	0.014	0.018	0.025
N =	715	715	715	715	661	661	506

* Dependent variable is the logarithm of net worth. Standard errors in parentheses. In Column (7), the sample is restricted to men who did not inherit their wealth.

In Column (3) we replace the average standardized beauty ratings with the matched ratings—the combination of gender and ethnically identical billionaires and raters. The estimated impact of perceived beauty is still very small (each one-standard deviation is associated with 2.4 percent greater net financial worth), and, while positive, the estimate is statistically insignificant. The results presented in Column (4) are based on a fully specified model using the matched set of beauty ratings. They differ little from those in Column (2), although beauty is positively, albeit not statistically significantly related to net financial worth, with a one-standard deviation higher beauty rating related to 4.9 percent higher wealth. The estimated impacts of the control variables hardly change from those presented in Column (2). The estimates in Columns (2) and (4) also change very little if we restrict the sample to Western or even further to U.S.-based billionaires.[13]

With only eight percent of the sample being female, it is difficult to draw useful inferences by estimating the equations separately for both men and women. Nonetheless, applying the specification in Column (4) to the small sample of female billionaires yielded a negative estimate of the impact of beauty, -0.093 (s.e. = 0.154), not surprisingly statistically insignificant. That this estimate is less than that for male billionaires, albeit not significantly so, is consistent with the summary of the literature in Hamermesh (2011, pp. 55-58).

Given the paucity of female billionaires, in Columns (5) and (6) we present the results of estimating the equations shown in Columns (2) and (4), restricting the sample to male billionaires. Again, the estimated impact of looks on net financial worth is small and statistically insignificant, although using the average based on matched ratings (men disaggregated by location/ethnicity) the estimate approaches statistical significance and is not tiny (with a one standard-deviation higher beauty rating associated with 6.3 percent greater wealth).

Two-thirds of the sample are billionaire males who did not inherit their wealth. Perhaps those members of this sub-sample who were more successful economically had used their looks to get further ahead. To examine this possibility, in Column (7) we present estimates of the expanded equation estimated over this smaller, less heterogeneous subsample. The results are slightly weaker than those shown in Column (6), with beauty having a positive but statistically insignificant (t = 1.32) relation to net financial wealth, and with the impact of greater educational attainment again being tiny (negative) and not statistically significant. If instead of only Western male raters we use all 13 Western raters, the beauty rating in this sub-sample has almost no impact (point estimate -0.012, t = 0.06), and the estimated impact of educational attainment remains negative and statistically insignificant. These results do not arise because of differences in male billionaires' beauty by inheritance status: The average beauty ratings are -0.039 and -0.059 among self-made and inheriting billionaires respectively, with a test of the difference between these averages yielding t = 0.40.[14]

To examine further the robustness of our essentially null results, we experimented with other specifications beyond those reported in Table 2. We added the standard deviation of the standardized ratings of each billionaire by the 16 students to the specification in Column (2) of Table 2, thus inquiring whether billionaires about whose looks the raters were more uncertain have greater or lesser financial assets. Including this additional variable hardly altered the estimated impact of the average beauty rating. Estimating the same specification 16 times using each rater's scores alone yields an average estimated impact of -0.008. Similarly, re-specifying the equation by substituting the standardized beauty rating averaged across the eight male raters does not qualitatively alter the conclusions from Table 2; and when we use only the average standardized rating across the eight female raters the results again change little. Finally, estimating median (least absolute deviations) regressions does not alter the conclusions.

4. Why such weak effects?

Beauty has been shown to improve success in the labor market and in other endeavors in a large variety of occupations, many of which involve populations of highly paid people. Citing only fairly recent studies, these include academics (Babin et al., 2020); celebrities (Gergaud et al., 2012); corporate directors (Geiler et al., 2018); economists (Hale et al., 2021); women professional golfers (Ahn and Lee, 2014); political candidates (Benjamin and Shapiro, 2009; King and Leigh, 2009; Jones and Price, 2017); regional political leaders (Ling et al., 2019); prostitutes (Arunachalam and Shah, 2012); NFL quarterbacks (Berri et al., 2011); professional speedboat racers (Yamamura et al., 2022), and professional tennis players (Bakkenbüll and Kiefer, 2015). These studies suggest a range of possible channels through which beauty might affect economic success, including discrimination ('lookism'), sorting and productivity.[15] With beauty clearly important in so many different areas, why

[13] In the sample of 548 Western billionaires the estimated coefficients on the average matched beauty rating and the indicator of college graduation are 0.072 (s.e. = 0.061) and -0.032 (s.e. = 0.081) respectively; in the sample of 278 U.S. billionaires the analogous estimates are 0.104 (s.e. = 0.080) and -0.142 (s.e. = 0.120).

[14] If we divide the sample of self-made male billionaires into thirds by age (<55; 55-67; 68+), the estimated effects of beauty are -0.0087 (s.e.= 0.092), 0.186 (s.e.=0.094), and 0.054 (s.e. 0.140) for the three tertiles respectively. The only estimate that is positive and reaches conventional levels of statistical significance (t=1.97) arises in the middle age range. We believe this is most likely a statistical artifact, as might be expected when carrying out a plethora of robustness checks. Since most of the self-made billionaires achieved that status well before age 55, it is difficult to see why the effect of beauty on the wealth of self-made billionaires should be negative at younger ages, but positive at older ages.

[15] Very little effort exists in the beauty literature to sort out causes of any observed impacts. The most successful such effort is a lab-experimental study (Möbius and Rosenblat, 2006).

do we find that, among billionaires, financial assets are essentially unrelated to beauty?

One possibility is that our ratings of beauty are random, consisting mostly of measurement error. This "beauty is in the eye of the beholder" caveat can be and has been raised with most such studies, and we cannot absolutely refute it. We should note, however, that the coherence among the views of the raters in this study is as high as that among raters in other studies in which multiple individuals judged looks based on photographs, and in which the averages of their ratings were strongly and significantly related to the subjects' economic outcomes. Thus, while there may be measurement error in the ratings, any errors are highly correlated across raters. This suggests that our raters perceive the billionaires' beauty the way the average adult does, and that something else is generating the absence of any estimated impact.

Another possibility is that measurement error contaminates the estimates of net financial wealth, thus generating the statistical insignificance of the relationships between wealth and beauty, and wealth and educational attainment. We examine this potential difficulty by obtaining information on those billionaires who were on the *Forbes* list in both 2008 and another year, 2018, and re-estimating the equations in Table 2 using the logarithm of their average net worth across these two years. The equations, estimated over 68 percent of billionaires in the 2008 sample, yield point estimates that are smaller and of even lesser statistical significance than those shown in Table 2. [16] Measurement error in the dependent variable does not appear to be an issue.

Still another possibility is that those billionaires included in the analysis—the 64 percent for whom photographs and information on their education were available—were nonrandomly selected from the entire 2008 *Forbes* list of 1125 billionaires. For this possible non-randomness to bias the results, it must also be the case that, at a given net worth, the billionaires were selected non-randomly along the dimension of their looks.

To examine this potential bias, we estimate a probit describing selection into the sample. This analysis shows that billionaires with higher net worth are significantly more likely to have had a photograph accompanying their *Forbes* profile (although the pseudo-R^2 is only 0.03). While the first necessary condition for bias thus exists, albeit only very weakly, there is no reason to believe that the second does. The photographs were not self-selected—it is not that good-looking (or bad-looking) billionaires were more likely to supply their portraits. Indeed, very few of the photos included were portraits. Instead, virtually all the images are news photographs, taken at public events such as media conferences, gala balls, sporting matches, and movie openings. The inclusion of photographs depended on what the *Forbes* journalists could find in their image archive, not on the willingness of billionaires to supply portraits.

Our results cannot be rationalized by measurement error in the crucial explanatory variable, measurement error in the dependent variable, nor sample selection. There is, however, a consistent explanation. Consider the process determining log wealth (W). The same equation could be written describing earnings.

$$Ln(W_i) = F(B_i) + G(X_i) + \alpha D_i + \varepsilon_i; F', G' > 0; F'', G'' < 0$$

where B is the beauty of individual i; X is a large vector of factors that determine wealth (e.g., education, age, experience, non-cognitive skills, etc.); D is a vector of fixed demographic characteristics (e.g., race, gender, location); and ε_i is the usual error term, assumed to be normally distributed. $F(B_i) + G(X_i) + \alpha D_i$ is the deterministic part of wealth.

Restricting the sample to $i \ni \{W_i \geq \$1b\}$, to individuals in the upper 0.0001 percent of households worldwide arrayed by assets (at least 4.5 standard deviations above the mean), we are selecting the sample by truncating the dependent variable very far into the right tail of its distribution. At this level, given the assumptions about F and G, the marginal impacts of beauty, B, or any variable X, will be tiny. That is exactly what we observe, for both beauty and education.

Based on the model in (1), we also expect that this highly truncated sample will be characterized by above average values of B and X. We do observe this for educational attainment. The 73 percent of the sample who graduated from college is much greater than the college graduation rate in the entire world population, and substantially greater even than that in wealthy Western economies.[17]

Are billionaires more beautiful than other adults of the same age? It is difficult to compare beauty in this sample to that in other samples; but we can base a rough comparison to the sample in Hamermesh and Parker (2005). They had six university students use a ten-point scale to rate the appearance of 94 university professors ages 29-73 based, as in the sample of billionaires, on photographs posted on the internet. Using their raw data, we matched billionaires to professors of similar ages, generating a comparison of the average raw ratings of the billionaires' looks (the ratings depicted in Fig. 1) to the average raw ratings of age-matched professors' looks. The average among billionaires in the age range 29-73 was 4.88 (s.e. = 0.04), slightly above that in the entire sample because the oldest billionaires are excluded here. Among the age-matched professors it was 3.97 (s.e. = 0.10). The billionaires were judged as being exactly one standard deviation more attractive than professors of the same age, with the difference being highly statistically significant. This admittedly loose comparison suggests, as our interpretation of the process predicts, that the billionaires are better-looking than others of the same age.[18] The reader might be concerned that the billionaires' greater financial resources enabled them to purchase much more and much better plastic surgery. Possible; but the evidence (Lee and Ryu, 2012) clearly suggests that plastic surgery produces only minor changes in others' perceptions of one's appearance.

In sum, within this restricted sample, wealth varies mainly due to differences in random draws from the extreme upper tail of the distribution of ε. It is unrelated to determinants of income generally—as we showed, to beauty and to educational attainment. However, those in this extreme upper tail of wealth are more educated and better-looking than the average person of the same age. They have higher values of those variables that generate economic success in the entire population.

F. Scott Fitzgerald's aphorism applies to billionaires too: "The [super-]rich are not like you and me." Studies of beauty and earnings among high income groups, such as business leaders and professional athletes, are still considering people whose economic position is far below the level of those in our study. Most people in those other studies are employees or must sell their services to the public or to an employer; the billionaires are almost entirely entrepreneurs of some kind. Given the role that chance plays in entrepreneurial accomplishments (Kerr, et al., 2014), extraordinary success as an entrepreneur is difficult to predict based on observable characteristics. (If it were otherwise, allocating venture capital would be considerably easier.) What is true of entrepreneurs in general is doubly true when distinguishing among leading entrepreneurs. If we focus on the world's top entrepreneurs, observables become almost irrelevant. Whether someone has assets five standard deviations above the mean or six standard deviations above the mean is rarely a matter of observables. This far along the extreme right tail of the distribution, luck dominates.[19] Our finding accords with Rule and

[16] 496 of the 727 billionaires who formed the basic sample in 2008 were among the 2,208 included in 2018. The probability of being on the *Forbes* list in 2018 conditional on being on the 2008 list was significantly lower among older billionaires and those with lower wealth in 2008; but the overwhelming majority of the variance in this probability was not explicable by variations in the billionaires' characteristics (pseudo-R^2 = 0.05).

[17] In the U.S. in 2008, 30 percent of adults ages 23 or over (the age range among the billionaires) had attained at least a college degree (calculated from the CPS-MORG, 2008).

[18] Restricting the sample to male billionaires ages 29-73 reduces the beauty gap between billionaires and matched university professors, but it remains large and highly statistically significant.

[19] Warren Buffett has emphasized the role of luck in his success, pointing out that he won the "ovarian lottery" by being born in the United States, and being

Table 3
Determinants of earnings among all workers, and among the top 0.1 percent, ACS 2018.

	(1)	(2)	(3)	(4)
	Males		Females	
	All	Top 0.1%	All	Top 0.1%
N =	1,240,692	1,289	1,011,936	1,099
Ind. Var.:				
Experience	0.058	0.002	0.050	0.0001
	(0.0002)	(0.001)	(0.0002)	(0.0011)
	[21.80]	[26.55]	[21.80]	[25.77]
Experience^2/100	-0.093	-0.002	-0.075	-0.0004
	(0.0004)	(0.002)	(0.004)	(0.00002)
White non-Hispanic	0.151	0.016	0.071	-0.001
	(0.001)	(0.008)	(0.002)	(0.006)
	[0.643]	[0.838]	[0.633]	[0.720]
Married	0.280	0.010	0.052	0.0003
	(0.002)	(0.012)	(0.002)	(0.010)
	[0.689]	[0.941]	[0.706]	[0.829]
High school	0.318	-0.061	0.383	-0.024
	(0.003)	(0.042)	(0.003)	(0.032)
	[0.359]	[0.025]	[0.304]	[0.064]
Some college	0.518	0.010	0.606	-0.004
	(0.003)	(0.041)	(0.003)	(0.031)
	[0.233]	[0.034]	[0.267]	[0.057]
College	0.964	-0.027	1.054	0.007
	(0.003)	(0.039)	(0.004)	(0.031)
	[0.202]	[0.352]	[0.234]	[0.318]
Graduate	1.249	-0.013	1.341	-0.010
	(0.003)	(0.039)	(0.004)	(0.039)
	[0.112]	[0.585]	[0.140]	[0.553]
Adj. R^2	0.331	0.033	0.272	0.001
Dep. Var. statistics				
Annual earnings (000$)				
Mean	$59.90	$697.47	$44.99	$604.74
99.9 percentile cut-off		$651.00		$543.00

*Dependent variable is the logarithm of annual earnings. Standard errors in parentheses, means in brackets. All estimates are based on sampling (person) weights.

Ambady (2008), who analyze Fortune 500 companies' CEOs, and find that within this highly selected group there is no significant relationship between attractiveness and their firms' revenues or profits.

To verify this explanation in a totally different context, consider earnings determination among employees in the U.S. Taking the American Community Survey 2018, we estimate a standard Mincerian earnings equation on large sub-samples (over 1 million respondents in each) of full-time (35+ hours per week) male employees and female employees. The results are shown in Columns (1) and (3) of Table 3, which present estimates of the impacts of the X variables, educational attainment, and a quadratic in potential experience (age minus years of schooling minus 6), along with those of the D variables, race/ethnicity and marital status. The parameter estimates are standard. Higher levels of education are associated with higher earnings. Men's earnings rise through 31 years of potential post-schooling experience, women's through 32 years in these cross-sections. Other things equal, there is a strong marriage premium among men, a much smaller premium among women. White non-Hispanic men earn about 16 percent more than otherwise identical minority men, white non-Hispanic women about 7 percent more.

What if we restrict these two samples to employees whose annual earnings place them in the top 0.1 percent of earners and estimate the same earnings equations? This restriction confines the sample to men with annual earnings of at least $652,000, and women with earnings of at least $543,000.[20] Note that while this sample is highly selected, the extent of selectivity is only 1/1000 of that which produced the sample of billionaires (some of whom enjoy a daily wealth increase of more than half a million dollars). As with the sample of billionaires, the top 0.1 percent of full-time employees in the American Community Survey are better educated and more experienced (older) than the average employee. Put another way, the characteristics that produce higher earnings in the population generate the sub-sample of very high-earning employees.

Within the sub-sample of high earners, however, differences in those characteristics do *not* produce differences in earnings. The estimates of the determinants of their earnings are shown in Columns (2) and (4) of Table 3. Differences in education in these sub-samples have no impact on annual earnings; and the effects of post-schooling experience are also tiny. Just as with the relationships between education and assets, and beauty and assets, in the previous section, so too here the outcome is mainly the result of randomness (or of the impacts of unobservables). When we truncate the dependent variable so that the sub-sample consists only of observations in the extreme right tail of the distribution, empirical regularities in earnings determination that are strong and significant within the full sample disappear entirely.

Ours is hardly the first study to find that well-established relationships vanish when the sample is selected from the extremes of the distribution. For example, looking more at the left tail of a distribution, Spivak and Damphousse (2006) find that, among inmates, education does not predict recidivism. Presumably this reflects the fact that prisoners, like extremely successful entrepreneurs, are a highly unusual subset of the general population. Likewise, and at the right tail of a distribution. studies of elite athletes tend to find that they are quite different from the general population on metrics such as body composition, strength, oxygen uptake and attitude. Yet among a group of elite performers, these characteristics do little to predict who will win a gold medal. For example, Brace et al. (2020) find that ultrarunners have a degree of mental toughness that is considerably beyond that of other sportspeople and the general population. Yet among elite ultrarunners, mental toughness ceases to predict of who will win a given race.

5. Conclusion

Among the ultra-rich, beauty and wealth are unrelated. The same is true for educational attainment and wealth. These findings are inherently interesting, since they stand in contrast to the strong relationships between physical attractiveness and economic success, and education and economic success, that have been documented in many other contexts. Our results, however, speak to a deeper methodological point: Statistical relationships that hold across broad populations may not persist within the extremes of the distribution. To illustrate this idea, we show that when a sample of U.S. employees is truncated to exclude the bottom 99.9 percent, the usual education-earnings and age-earnings relationships disappear. To experienced econometricians, this finding might be unsurprising. The literature on the impact of truncating a dependent variable goes back at least to Heckman (1976). Its implications for empirical research are, however, easily forgotten.[21]

The impact of truncating the dependent variable is relevant not only to wealth and earnings. We might expect it to affect studies of the relative success of other elite groups, such as Olympic athletes, Nobel prize winners, Hollywood stars, and *Fortune* 500 CEOs. At the opposite tail of these distributions, the same statistical difficulty may also affect analyses of the determination of economic outcomes among especially disadvantaged groups, such as the long-term homeless, the persistently unemployed, habitual drug users, and people with chronic health problems. Luck matters more at the extremes. When we sample only from the tails, the world becomes less predictable.

born in an era where the economy provides outsize rewards for someone with a talent for valuing businesses (Martin, 2018).

[20] Limitations of sample sizes prevent going still further up the distributions of earnings.

[21] They are also widely ignored in the popular media, as illustrated by stories touting a very high representation of college dropouts among billionaires (e.g., Johnson Hess, 2017).

References

Ahn, S.C, Lee, Y.H., 2014. Beauty and productivity: the case of the ladies professional golf association. Contemp. Econ. Policy 33, 155–168.
Arunachalam, R., Shah, M., 2012. The prostitute's allure: the return to beauty in commercial sex work. B.E. J. Econ. Analysis & Policy 12 (1) Article 60.
Babin, J.J., Hussey, A., Nikolsko-Rzhevsky, A., Taylor, D., 2020. Beauty premiums among academics. Econ. Educ. Rev. 78 Article 102019.
Baghic, S., Svejnar, J., 2015. The effect of billionaire wealth, income distribution, and poverty. J. Comparative Econ. 43, 503–530.
Bakkenbüll, L-B., Kiefer, K., 2015. Are attractive female tennis players more successful: an empirical analysis. Kyklos 68, 443–458.
Benjamin, D., Shapiro, J., 2009. Thin-slice forecasts of gubernatorial elections. Rev. Econ. Stat. 91, 523–536.
Berri, D., Simmons, R., van Gilder, J., O'Neill, L., 2011. What does it mean to find the face of the franchise? Physical attractiveness and the evaluation of athletic performance. Econ. Letts. 111, 200–202.
Biddle, J., Hamermesh, D., 1998. Beauty, productivity and discrimination: lawyers' looks and lucre. J. Labor Econ. 16, 172–201.
Borland, J., Leigh, A., 2014. Unpacking the beauty premium: what channels does it operate through, and has it changed over time? Econ. Record 90, 17–32.
Brace, A., George, K., Lovell, G., 2020. Mental toughness and self-efficacy of elite ultra–marathon runners. PLOS One 15, e0241284.
Castaldi, C., Milaković, M., 2007. Turnover activity in wealth portfolios. J. Econ. Behav. Organization 63, 537–552.
Dolan, K.A., 2012. Methodology: How we crunch the numbers. Forbes March 7.
Freund, C., Oliver, S., 2016. The origins of the superrich: the billionaire characteristics database. Petersen Institute for Int. Econ. 16 Working Paper-1.
Geiler, P, Renneboog, L., Zhao, Y., 2018. Beauty and appearance in corporate director elections. J. Intl. Financial Markets, Institutions, and Money 55, 1–12.
Gergaud, O., Ginsburg, V., Livat, F., 2012. Success of celebrities: talent, intelligence or beauty? Econ. Bull. 32, 3120–3127.
Hale, G., Regev, T., Rubinstein, Y., 2021. Do looks matter for an academic career in economics? In: CEPR dp 15893.
Hamermesh, D., 2011. Beauty pays: Why attractive people are more successful. Princeton University Press, Princeton, NJ.
Hamermesh, D., Parker, A., 2005. Beauty in the classroom: instructors' pulchritude and putative pedagogical productivity. Econ. Educ. Rev. 24, 369–376.
Hamermesh, D., Abrevaya, J., 2013. 'Beauty is the promise of happiness'. Eur. Econ. Rev. 64, 351–368.
Heckman, J., 1976. The common structure of statistical models of truncation, sample selection and limited dependent variables and a simple estimator for such models. Annals Econ. Soc. Measurement 5, 475–492.
Johnson Hess, A., 2017. 10 Ultra-Successful Millionaire and Billionaire College Dropouts. CNBC May 10.
Jones, T., Price, J., 2017. Information and the beauty premium in political elections. Contemp. Econ. Policy 35, 677–683.
Kamakura, W., Jones, W., 2014. Race, ethnicity, and acculturation: How racially matched images influence subsequent perceptions of beauty. SSRN Electronic J.
Kaplan, S., Rauh, J., 2013. Family, education, and sources of wealth among the richest Americans 1982-2012. 1982-2021. Am. Econ. Rev., Papers and Proceedings 103, 158–162.
Kerr, W.R., Nanda, R., Rhodes-Kropf, M., 2014. Entrepreneurship as experimentation. J. Econ. Perspectives 28, 25–48 Summer.
King, A., Leigh, A., 2009. Beautiful politicians. Kyklos 62, 579–593.
Kroll, L., 2006. Fortunes of kings, queens and dictators. Forbes May 5.
Kroll, L., 2008. Billionaires 2008. Forbes, Mar 6.
Lee, S., Ryu, K., 2012. Plastic surgery: investment in human capital or consumption? J. Human Capital 6, 224–250.
Ling, L., Luo, D., She, G., 2019. Judging a book by its cover: the influence of physical attractiveness on the promotion of regional leaders. J. Econ Behavior & Organization 158, 1–14.
Liu, X., Sierminska, E., 2014. Evaluating the effect of beauty on labor market outcomes: A review of the literature. IZA dp 8526.
Martin, E., 2018. Here's why Warren Buffett says that he and Charlie Munger are successful. CNBC May 5.
Monk, E., Esposito, M., Lee, H., 2021. Beholding inequality: race, gender, and returns to physical attractiveness in the United States. Am. J. Soc. 127, 194–251.
Möbius, M., Rosenblat, T., 2006. Why beauty matters. Am. Econ. Rev. 96, 222–235.
Moretti, E., Wilson, D., 2022. Taxing billionaires: estate taxes and the geographical location of the ultra-wealthy. Am. Econ. J.: Econ. Policy forthcoming.
Raub, B., Johnson, B., Newcomb, J., 2010. A comparison of wealth estimates for America's wealthiest decedents using tax data and data from the Forbes 400. National Tax Association, Proceedings, 103, 128–135.
Rule, N., Ambady, N., (20080. The face of success: inferences from chief executive officers' appearance predict company profits. Psych. Sci. 19, 109-111.
Saez, E., Zucman, G., 2016. Wealth inequality in the United States since 1913: evidence from capitalized income tax data. Q. J. Econ. 131, 519–578.
Scholz, J.K., Sicinski, K., 2015. Facial attractiveness and lifetime earnings: evidence from a cohort study. Rev. Econ. Stat. 97, 14–28.
Sierminska, E., 2015. Does it pay to be beautiful?. IZA World of Labor.
Spivak, A., Damphousse, K., 2006. Who returns to prison? A survival analysis of recidivism among adult offenders released in Oklahoma. 1985–2004. Justice Res. Policy 8, 57–88.
Yamamura, Y., Hayashi, R., Tsutsui, Y., Ohtake, F., 2022. Racers' attractive looks, popularity, and performance: how do speedboat racers react to fans' expectations? Jap. Econ. Rev. 73 forthcoming.