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BEAUTY AND THE LABOUR MARKET

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ABSTRACT

We develop a theory of sorting across occupations based on looks and derive its implications for testing for the source of earnings differentials related to looks. These differentials are examined using the 1977 Quality of Employment, the 1971 Quality of American Life, and the 1981 Canadian Quality of Life surveys, all of which contain interviewers' ratings of the respondents' physical appearance. Holding constant demographic and labor-market characteristics, plain people earn less than people of average looks, who earn less than the good-looking. The penalty for plainness is 5 to 10 percent, slightly larger than the premium for beauty. The effects are slightly larger for men than women; but unattractive women are less likely than others to participate in the labor force and are more likely to be married to men with unexpectedly low human capital. Better-looking people sort into occupations where beauty is likely to be more productive; but the impact of individuals' looks on their earnings is mostly independent of occupation.

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He [Aristotle] used to say that personal beauty was a better introduction than any letter. Diogenes Laertius, <u>The Lives and Opinions of the Eminent Philosophers</u> (ca. 200 A.D.)

I. Introduction

Discrimination in the labor market has generated immense amounts of research by economists. Many alternative theoretical analyses of the nature of discrimination and a vast empirical literature have been produced. (See, e.g., Cain's, 1986, review.) In the U.S. alone careful empirical studies of possibly discriminatory outcomes involving blacks, Hispanics, women, linguistic minorities, physically handicapped workers and no doubt others have been produced.[1] Our purpose here is to offer the first study of the economics of discrimination in the labor market against yet another group --- the ugly --- and its obverse, possible favoritism for the beautiful. We examine whether there is a reduced-form combination of attitudes toward beauty and a distribution of workers among jobs that generates apparently discriminatory labor-market outcomes.

This analysis is interesting in its own right. Every worker brings some physical attractiveness to the labor market along with other attributes, and most are concerned, perhaps inordinately so (Wolf, 1991), with this aspect of their labor-market characteristics. Interest in "lookism, ... the construction of a standard of beauty/attractiveness," is an expression of a belief that people failing to meet that standard are mistreated. Antidiscrimination legislation has been proposed elsewhere to prevent denying employment on the basis of "facial features, build and height;" and in the U.S. a case law in this area is developing and likely to burgeon under the Americans with Disabilities Act of 1990.[2]

Studying possible discrimination on the basis of looks should also be of broader interest. It is very difficult to construct a research design that allows one to distinguish labor-market outcomes arising from discrimination against a group from those produced by intergroup differences in unobserved (by the researcher) productivity. In the case of looks we may have a better chance of doing so, for we can identify activities in which looks are likely to be more important, and thus where the payoff to beauty (or penalty for homeliness) reflects differences in productivity. In the literature on discrimination this provides a rare example of going measurement of the extent of discrimination to examining its sources (but see also Dillingham et al, 1994).

In Section II we examine some relevant results of social–psychological studies of beauty and human behavior, aiming toward considering whether it is possible to use measures of beauty as if they were objective descriptions. Section III presents a model in which beauty is rewarded in the labor market and affects workers' choice of occupations. Section IV describes the three sets of microeconomic data that we use to analyze the role of looks. Section V tests for the presence of earnings differentials based on looks; Section VI examines possible causes for male–female differences in the effects of beauty; and Section VII conducts tests aimed at distinguishing the sources of wage differences by looks.

II. Background

If there is no common agreement on what constitutes beauty, it makes no sense to consider the role of looks in the labor market. Fortunately, a huge literature exists on this subject, including research by anthropologists, sociologists and social psychologists, that has recently been ably summarized (Hatfield and Sprecher, 1986). It seems quite clear that there are few consistent standards of beauty across cultures. Hugely distended lower lips are considered attractive by Ubangi men; women's bound feet by Manchu dynasty men; and other less extreme examples of differences in standards of beauty across cultures could easily be cited.

What is perhaps a bit less obvious is that standards of beauty change over time within the same culture, changes that go beyond preferences and fads in clothing to the question of body type. The Rubens ideal looks much different from her Northern European counterpart walking down the runway at a modern Paris salon. Today's ideal lean Western male would have been viewed as potentially or actually consumptive and a bad match in both marriage and labor markets in nineteenth–century America. The crucial issue for our purposes is whether standards of attractiveness change slowly enough to allow labor–market decisions related to beauty to be planned for a horizon as long as a person's expected working life.

The evidence seems quite clear on this issue: Within a culture at a point in time there is tremendous agreement on standards of beauty, and these standards change quite slowly. For example, respondents ranging in age from seven to fifty who were asked to rank the appearance of people depicted in photographs showed very high correlations in their rankings. Moreover, the ratings of the appearances of a group of individuals photographed at different stages of their adult lives were highly autocorrelated (Hatfield and Sprecher, 1986, pp. 282–3).

Some explicit evidence on this is provided by the tabulations in Table 1. This Canadian survey was conducted in 1977, 1979 and 1981, with different interviewers in each year asked to "categorize the respondent's physical appearance" into one of the five rubrics: Strikingly handsome or beautiful; above average for age (good looking); average for age; below average for age (quite plain); and homely. The data have some aspects of a panel, so that many of the respondents were interviewed in two adjacent years, and some appear in all three years.

The two–year transition matrices in the upper part of Table 1 are highly nonrandom, as shown by the χ^2–statistics based on the contingency tables implicit in them. In each there is much more clustering along the prime diagonal than would arise randomly. The lower part of Table 1 provides information on the constancy of the interviewers' ratings over three biennia. Nearly 93 percent of the respondents are rated identically in at least two years and only one rating level different in the third year.[3] These data suggest that there is substantial positive correlation in how people rate others' looks.

There has been some examination by non–economists of some of the empirical labor–market correlates of beauty. The best of these is probably Quinn (1978), who generated simple correlations of interviewers' ratings of the looks of respondents who were full–time employees with their incomes using one of the data sets we employ. Incomes were higher among both men and women the higher was the assessment of the respondent's looks, based on a three–point rating of beauty. The results held for both genders, and there was no evidence of asymmetry in the effect on income of departures from the middle category. A similar study (Roszell et al, 1989) used the Canadian data underlying Table 1 to regress 1981 income on 1979 income and a variable rating the respondent's looks, with results implying faster income growth among better–looking respondents.

Several studies have examined correlations of earnings with the appearance of workers in a narrow age and/or occupational cohort. A recent good example is Frieze et al (1991), who studied earnings of MBAs over the first ten post–degree years. Ratings of beauty based on photographs of the students while in school were correlated positively with both starting and subsequent salaries for males. Among females there was no correlation with starting salary, but more attractive women experienced more rapid salary growth.[4]

A related larger literature has offered hypothetical résumés of potential workers along with photographs and asked experimental subjects to choose among these workers for various jobs (Hatfield and Sprecher, 1986). Among men beauty enhanced the worker's likelihood of being chosen for both clerical and professional/managerial jobs. Beauty helped the women's chances of being selected only for the higher–level clerical jobs.

We can be fairly sure that within modern Western society standards of beauty are both commonly agreed upon and stable over one's working life. The evidence also suggests that women's and men's beauty/ugliness might be treated differently in the labor market, so that any empirical study must analyze men and women separately. Most important, an examination of the literature makes it clear that there has been little systematic thought about the role of beauty in the labor market, and that the empirical analysis of this issue has been limited to tabulations and regressions holding at most one or two variables (usually age) constant.

III. A Model of Looks and Occupational Choice

Our approach to modeling the existence of looks–based differences in labor– market outcomes assumes that in some occupations attractive workers may be more productive than unattractive workers. This "productivity" advantage could arise from customer discrimination, with consumers preferring to be served by better–looking individuals; or there may be occupations where physical attractiveness enhances the worker's ability to engage in productive interactions with coworkers. Prima facie evidence supporting this assumption is provided by a recent survey of employers (Holzer, 1993), who were asked "How important or unimportant is attractive physical appearance [for the job most recently filled]?" Eleven percent responded that appearance was very important, while 39 percent felt that it was somewhat important.

We begin by assuming an economy with two occupations, one in which beauty enhances productivity, one in which it does not. There is also one other factor that affects productivity in both occupations, but which may be more important in one sector than another. Wages in the two occupations are given by:

$$w_{1i} = a_1 x_i \ ;$$
$$w_{2i} = a_2 x_i + b_i \ ,$$

where i refers to an individual and a_1, $a_2 > 0$. Attractiveness is measured by b, which takes the value 1 for half the population (attractive workers) and -1 for the other half (unattractive workers). The other productivity-enhancing characteristic x takes the value of 1 for half the population and 0 for the other half. Assume finally that x and b are independently distributed, so that there are four equal-sized groups of workers.

Since workers seek to maximize income, they choose Occupation 1 if $w_{1i} - w_{2i} > 0$, or $[a_1 - a_2]x_i > b_i$, and Occupation 2 otherwise. If $|a_1 - a_2| < 1$, there is no mixing; all attractive workers choose Occupation 2 and all unattractive workers choose Occupation 1. The average wage for attractive workers is $.5a_2 + 1$, while the average wage for the unattractive is $.5a_1$. There is a measured looks differential in this economy whether or not one controls for x; but that differential is identical to the wage premium for working in Occupation 2.

If $a_2 - a_1 > 1$, some unattractive workers (those with $x=1$, $b=-1$) choose Occupation 2, as do all attractive workers. The rest of the unattractive population chooses Occupation 1. In this situation the average wage for attractive workers is still higher than the average wage for unattractive workers: $E[w|b=1] = .5a_2 + 1$, while $E[w|b=-1] = .5a_2 - .5$. There is also a differential within Occupation 2 between the attractive and the unattractive: The average wage of attractive workers in Occupation 2 is $.5a_2 + 1$, while the average wage for unattractive workers there is $a_2 - 1$. If one does not condition on x, there will appear to be a premium for unattractive workers who have jobs in the "beautiful" occupation, and if $a_2 > 4$, unattractive workers in Occupation 2 will earn more than the average wage for attractive workers. If one does condition on x, the looks differential within Occupation 2 will be the same as the looks differential for the economy as a whole.

If $a_2 - a_1 > 1$, the occupation that rewards beauty also gives a relatively high reward for the productivity-enhancing factor, leading unattractive workers with large endowments of that factor to accept the looks penalty to get the higher return for the factor. This positive selection may make it seem as though there is a pay premium for unattractive workers in the occupation dominated by their better-looking counterparts.

When $a_2 - a_1 < -1$, all unattractive workers choose Occupation 1, as do all attractive workers with $x = 1$. The average wage for attractive workers remains above the average wage for unattractive workers, with $E[w|b=1] = .5a_1 + .5$, and $E[w|b=-1] = .5a_1$. If one does not condition on x, there appears to be a gain to the attractive workers from mixing with the unattractive, as the wage for attractive workers in Occupation 1 is a_1, greater than the wage of 1 earned by the attractive workers in Occupation 2. The looks differential in Occupation 1 will be greater than the overall looks differential only if $a_1 > 2$.

In this simple model there is no case in which both occupations will be integrated; but adding a second x to the model generates cases with mixing in both occupations. In general, a model with many x's and many occupations would have unattractive workers locating where beauty is rewarded whenever those occupations also give a high relative reward to some other characteristic with which the unattractive worker is abundantly endowed. Obversely, an attractive worker would choose an occupation which did not reward beauty if it provided a high relative reward for that worker's particular bundle of other characteristics.

The discussion has assumed no correlation between b and x. The mixing and the differences in differentials arise from features of technology — — — is there an occupation that rewards attractiveness and also happens to give a relatively high reward to some other factor? Introducing a correlation between x and b into the simple model does not change the conclusions about the values of the a's for which mixing will or will not occur. It does, though, affect pay differentials in obvious ways. For example, if x and b are positively correlated and there is sorting of some unattractive workers into occupation 2, the overall looks differential will remain larger than the differential within occupation 2, but both will grow in absolute value.

An obvious alternative to a model with productivity or consumer discrimination generating looks–based differences in labor–market outcomes has them resulting from employer discrimination against the unattractive. A Becker–type model with employers' distaste for unattractive employees produces a looks differential in earnings, but no systematic sorting of workers into occupations on the basis of appearance. Alternatively, a model with employers discriminating against the less attractive only when filling certain positions leads to a looks differential resulting from occupational crowding. Such a model also implies sorting into occupations on the basis of attractiveness, although it does not indicate a priori which occupations should exhibit concentrations of attractive or unattractive people. However, in the occupational–crowding model the unattractive worker who obtains a job in one of the occupations ordinarily reserved for the attractive suffers no earnings penalty — — — the looks differential is linked to occupations, not individuals.

Is it possible to distinguish empirically between the model we have presented and an employer–discrimination or occupational–crowding model? In theory the answer is yes, but in practice it may be quite difficult. Consider the simple model with two occupations and two x's. If we could control for both x's, we would find unattractive workers earning less than attractive workers only in certain occupations (contrary to the Becker model). The unattractive worker could not achieve a wage gain by moving into an occupation dominated by attractive workers (as he or she could in an occupational–crowding model). In a wage regression that included the x's, attractiveness and occupational dummy variables and interactions between them, the Becker model should produce a non–zero coefficient only on the attractiveness dummy; the crowding model only on the occupational dummy; and the productivity model only on the interaction term.

The reliability of such a test would be compromised, however, if one of the x's was not observed. For example, if the unobserved x received a relatively large reward in the occupation that also rewarded attractiveness, the regression described above could produce non–zero coefficients on the occupational and attractiveness dummies as well as on the interaction term.[5] This could also occur if looks differentials in the labor market were the result both of employer discrimination against the unattractive and productivity advantages to the attractive in some occupations.

Beyond problems related to unobserved variables are those associated with identifying occupations where employer discrimination against the unattractive might exist, or alternatively, those where attractiveness might lead to greater productivity. To the extent that the latter occupations are identifiable, finding that more attractive workers were more heavily concentrated in such occupations would support the productivity model.

Our empirical strategy is guided by the productivity model. We first determine whether standard earnings equations yield a looks differential, and then whether that differential differs across occupations in ways the model suggests. In addition, we look for evidence of the sorting implied by the productivity model, checking whether more attractive workers tend to be concentrated in those occupations where one might suspect that attractive people have a productivity advantage. We present the productivity model to illustrate that the existence of looks differentials does not necessarily result from employer discrimination against the unattractive. Discovering evidence in favor of this model does not, though, disprove the existence of such discrimination.

IV. Data

Two broad household surveys for the U.S. and one for Canada provide data on the respondents' looks as well as on the usual labor–market and demographic variables of interest to economists. The 1977 Quality of Employment Survey (QES) contains information on 1515 workers. This Survey has the advantage of including great detail about labor–market behavior, but the disadvantage of including only labor–force participants. The second American data set is the Quality of American Life survey (QAL) in 1971, which contains interviews of 2164 respondents. For our purposes this study has the advantage of having substantial background information on the respondents, but the disadvantage of containing relatively fewer variables describing the worker's job than does the QES. The Canadian Quality of Life study (QOL) contains 3415 observations in 1981. This study has none of the disadvantages of the two American data sets and the additional attraction of providing (for a much smaller subsample that constitutes a three–year panel) three observations on each respondent's looks.

All three surveys asked the interviewer to "rate [or categorize] the respondent's physical appearance" on the five–point scale shown in Table 1, along which looks range from strikingly handsome or beautiful to homely.[6] The distributions of the ratings in the three surveys are shown in Table 2. (For the Canadian data we present averages based on all the respondents included in the three–year study.) Among both men and women roughly half are rated as average; and many more are rated above–average than are viewed as below–average. Either Canadians are better–looking than Americans; or Canadian interviewers (perhaps the populace generally) are less willing to describe someone as having below–average looks. What is most interesting is that the ratings of women are more dispersed around the middle category.

This is a common finding in the social–psychological literature: Women's appearances evoke stronger reactions, both positive and negative, than do men's (Hatfield and Sprecher, 1986).

Very few people are rated as strikingly beautiful (handsome) or as homely. Thus while we make some use of the full five–point scale, in most of the work we use the three–fold distinction above–average, average and below–average. Even this means that the cell sizes for some of the categories, e.g., below–average looking people in the QAL, are not very large.

All three surveys offer a variety of measures of earnings. In all of them we chose to calculate hourly earnings as annual earnings divided by 52 times weekly hours.[7] In the analyses involving hourly earnings all respondents who worked less than 20 hours per week and who earned less than $.75 per hour in the QAL ($1 per hour in the QES and the QOL) are excluded, as are the self–employed and all those for whom data on the various control variables are unavailable.[8] The empirical work people includes only workers ages 18–64.

Other variables defined for the analyses of hourly earnings and included in all three data sets are: marital status (which we measure as a zero–one dummy variable, married or not); education, defined as a vector of dummy variables measuring high–school completion, some college, or a college degree or more; and one–digit industry. Self–reported health status is included in all the regressions. Most important, anyone whose health status in the QES is listed as "totally and permanently disabled" or the next most severe category on a seven–point subjective scale is excluded from all the empirical work. In the QAL a respondent is excluded if health "prevents him/her from doing lots of things," while in the QOL anyone whose self–reported health status is not at least rated as "fair" is excluded.[9] These exclusions minimize any spurious results stemming from a possible correlation between physical appearance and major physical disabilities that reduce productivity.

Since the purpose is to control for as many other causes of variation in earnings as possible, we define the set of regressors quite broadly. In the QES and QOL the data allow the construction of actual labor–market experience, years of tenure with the firm, and an indicator of union status. In the former establishment size is included, while the latter includes firm size. In the QAL experience is measured as age – schooling – 6. In estimates based on the two American data sets we include dummy variables for race and for location in the South, while in the QOL we include a vector of variables for Canada's regions and an indicator of whether the person does not speak English at home. Finally, the QAL allows us to include measures of the respondents' fathers' occupations, of their early childhood background and of their immigrant status and that of their parents and grandparents.

V. Looks and Earnings

The most interesting economic question involving beauty is probably its relation to an individual's economic success. In Section III we suggested three possible reasons for a premium for beauty or a penalty for ugliness in the labor market: Pure employer discrimination, customer discrimination/productivity, and occupational crowding. In order to examine these we need to know first whether earnings differentials based on beauty even exist.

We make no claim to be able to estimate a structural model of a hedonic market for looks. Rather, in the first part of this Section we present estimates of standard earnings equations that allow for the possibility of differences in earnings related to looks. In the final part we synthesize the findings to infer what we have learned from this approach about the existence of such earnings differentials.

A. Estimates of the Relationship of Looks and Earnings

Columns (1) and (4) of Table 3 present estimates of earnings equations based on the data from the QES and on a three-point rating of beauty. Columns (1) and (5) of Table 4 do the same using data from the QAL, as do columns (1) and (5) of Table 5 for the QOL. In these and subsequent tables we present the probabilities (p) related to the F-statistic testing the joint significance of the variables reflecting individuals' beauty.

Of the six equations we find that the pair of beauty variables is jointly significantly nonzero at some conventional level in four cases. Moreover, in all six groups people with above-average looks receive a pay premium, ranging from as little as 1 percent to a high estimate of 13 percent (for women in the QAL). In five groups (excluding only women in the QAL) workers with below-average looks receive a pay penalty, ranging from 1 percent to as large as 15 percent. Not all of these individual coefficients are significantly different from zero. Many are, though; and the consistency of the pattern across three independent samples suggests that the finding of pay premia and penalties for looks is robust.

The estimates based on the QES indicate that more attractive people are paid more. However, the premia for good looks are considerably smaller than the penalties for bad looks and are not statistically significant. The results for men are corroborated by the QAL results in Table 4, with positive estimated coefficients for above-average looks categories and (larger) negative wage penalties for those in below-average looks categories. They are, though, contradicted by the estimates from the QOL in Table 5. In that sample there is a significant premium for good-looking men, but a tiny and insignificant penalty for men of below-average looks. A similar disagreement exists in the estimates for women. The large penalties for ugliness in the QES are replicated in the Canadian QOL, but are contradicted by a positive coefficient for below-average looking women in the QAL. The small premia for above-average looking women in those two samples are also contradicted by the statistically significant and large premium for attractiveness in the QAL.

The similarity of the premia and penalties across the two genders is also interesting. In the results from the QES they are nearly identical. In the QAL there is a larger penalty for below-average-looking men than for women, but a larger premium for good-looking women. The opposite pattern holds in the QOL. Among people who choose to work at least half time, beauty does not generate hugely different effects on the earnings of women and men.

While the results are qualitatively similar in the three samples, one might worry still more about the robustness of the estimates. One concern is that each interviewer might have a different standard for beauty. These differences could be regarded as a form of measurement error, lowering the efficiency of our estimates and biasing them to the extent that interviewer standards were spuriously correlated with respondents' earnings. To account for any potential problems this might cause, columns (2) and (6) of Tables 4 and 5 reestimate these reduced-form earnings equations using interviewer-specific fixed effects for the QAL and QOL respectively. Among men the penalty for ugliness increases slightly in both samples; but the changes in the premium for good looks are in opposite directions. Among women the unexpected positive effect of below-average looks becomes larger, but none of the other estimates of penalties and premia is affected much. Taken together, the results suggest clearly that the relation between looks and earnings does not arise from idiosyncratic ratings by particular interviewers.[10]

Another worry is about variables that are necessarily excluded from some or all of the samples because they are unavailable. Obviously, variables in the latter group cannot be examined here. But in the former group we can consider the impact of excluding the worker's family background and intelligence. Including the family background measures from the QAL, as in Table 4, lowered the absolute values of the estimated looks premia and penalties by less than .005 for men, and by less than .02 for women. Had we also included in columns (1) and (5) of Table 4 a dummy variable for workers whose IQ was rated by the interviewer as being in the top 7 percent, the absolute values of the coefficients for men would fall by .002 each and those for women would fall by .006 each. Despite the positive correlation between IQ and beauty, the changes are tiny. They do not alter the inferences from Table 4 or from the estimates based on the other data sets.

Columns (2) and (5) in Table 3 ((3) and (7) in Table 4) estimate the relationship between hourly earnings and looks using the complete five–point rating scheme. For men in the QES the results are remarkable: Hourly earnings rise with each successively higher rating of a worker's appearance. Among women in the QES and men in the QAL this is true except for strikingly handsome or beautiful workers. For women in the QAL the monotonic relationship is broken by the earnings premium received by plain women. Using the five–fold distinction adds little to the ability to explain hourly earnings (increasing the $\bar{R}^2$ in two cases, decreasing it in two others); and it in no way alters our conclusions about premia and penalties for looks.

A long, large and still growing literature (e.g., Taubman, 1975; McLean and Moon, 1980; and Averett and Korenman, 1993) has studied the relation between weight and/or height and earnings. We can test whether our results merely demonstrate that these few bodily characteristics explain the beauty penalties and premia by including measures of height and weight in the earnings equations. In the QES the interviewer rated the respondent's weight on a five–point scale and estimated the respondent's height in inches, while only height is available in the QAL.[11] For both samples we formed dummy variables based on height, categorizing women as tall if they exceeded 5'9" (6' for men) or short if they were below 5' (5'6" for men). Self–explanatory dummy variables for people who are obese, or only overweight, were constructed for the QES sample.

The results of adding these measures to the earnings regressions that contain the three–fold rating of beauty are shown in columns (3) and (6) of Table 3 and columns (4) and (8) of Table 4. Other than wage premia for both short and tall women in the QAL and a penalty for short men in the QES none of these variables has a coefficient that exceeds its standard error. Most important, including these measures of body type has little effect on the coefficients on the ratings of beauty in all four samples –– much too small to suggest that the relationship between looks and earnings arises from any possible correlation between appearance and height or weight.

The Canadian data allow us to examine whether additional information about an individual's looks beyond that contained in a rating by one interviewer adds to our ability to infer the impact of looks on earnings. For the subset of respondents included in the bottom part of Table 1 the study provides three independent estimates of an individual's looks. One approach to using this information would be to create a set of dummy variables for each of the ten combinations of looks ratings based on the three–fold classification for each of the three years. This has the difficulties of producing a few very sparsely occupied cells and of ignoring information contained in the five–fold classification.

An alternative approach uses the interviewers' ratings to infer the respondents' underlying beauty. Denote the individual's true beauty by B. Let B be normally distributed n(0,1), an arbitrary scaling that does not affect the results (Terza, 1987). For any particular year we assume that the interviewer assigns a rating along the five–point scale based on her estimate of B. The information in Table 2 for the entire population implies that the informational content of a person's rating as homely, for example, is that the person is in the lowest 2.5 percent of the population. The best estimate of that person's B is $\hat{B} = E(B \mid B < N^{-1}(.025))$.[12] Similar inferences can be drawn based on partitioning the normal distribution for each of the other ratings using the population percentages in Table 2.

Given the inference about B for one year, an estimate of a respondent's true beauty is B^*, the average of the three independent estimates $\hat{B}$. To illustrate what this scheme implies, consider an example of the underlying beauty of a particular pair of respondents. One person is rated as average in all three years (like 26.3 percent of the sample members); the other is rated as above average in one year, average in another and below average in the third (like 1.0 percent of the sample). Because few respondents are rated below average, we infer that the second person's true beauty is less than the first person's.

We calculate B^* for each sample member used in the estimates in Table 5 who was in the panel for all three years. Columns (3) and (6) of Table 5 present estimates on this narrower sample using linear and quadratic terms in the $\hat{B}$ for 1981.[13] Columns (4) and (8) replace the estimate of beauty for 1981 by the beauty index B^* based on all three years of information about the worker's looks. This substitution adds to the significance of the equations for both men and women. Obtaining additional information on a worker's beauty provides additional information about his or her earnings. Workers whose beauty is estimated to be higher earn more, and the marginal impact of additional beauty is diminishing. Here there is an asymmetric effect of looks on earnings, with lesser rewards for additional beauty and increasing penalties for increasingly bad looks.

B. Synthesis of the Basic Results, and an Initial Interpretation

Tables 3–5 stand on their own and provide the basic evidence for the existence of earnings differentials based on beauty. Nonetheless, it is useful to summarize the results to infer what the three sets of data imply are the best estimates of the penalties and premia associated with looks. Table 6 presents such summaries, for both genders separately and for the entire set of observations, and for all three samples combined and for the two American samples alone. The estimates are from regressions that pool the samples in Tables 3−5 (or Tables 3 and 4 only) and that allow the regression coefficients on all variables other than the beauty measures to differ across the samples. Pooling the samples for men and women alone is not rejected by the data; and for each gender both the penalty and premium are significantly nonzero. Indeed, even pooling the data for both genders for all three samples is not rejected; and the penalties and premia in both sets of pooled equations are all significantly nonzero.

The results make it clear that there is a significant penalty for bad looks among men. The 9 percent of working men who are viewed as being below average or homely are penalized about 10 percent in hourly earnings, other things equal. The 32 percent who are viewed as having above−average looks or even as handsome receive an earnings premium of 5 percent. Among women there is some evidence of a premium for good looks, with an average effect of about 4 percent; the penalty for bad looks (for the lowest 8 percent of working women) is only 5 percent. Among women neither effect alone is highly significant, though they are jointly significant. Finally, the combined results in the bottom two rows suggest a 7 to 10 percent penalty for being in the lowest 10 percent of looks among all workers, and a 5 percent premium for being in the top 30 percent.

While the absolute values of the point estimates of the penalties generally exceed the estimates of the earnings premia, these differences are not significant. There is only weak evidence of asymmetry in how the labor market treats ugliness and beauty.[14]

Some might interpret our results as merely showing that the unobserved determinants of productivity generate extra earnings that are used to improve a worker's beauty. There is the conventional problem associated with any hedonic estimation, i.e., those with higher wages holding constant the observables will choose to invest more in beauty. Unfortunately, as is usual, our data are not rich enough to permit a credible simultaneity correction. Two arguments, though, suggest the problem is not crucial here. First, the social–psychological evidence we mentioned in Section II showed how little individuals' relative physical appearances change during adulthood. That suggests there is limited scope for using unexplained earnings differences to "buy" differences in beauty. Second, and more telling, if differences in unexplained earnings were used to affect beauty ratings, their persistence over a working life should lead to a greater simultaneity bias among older than among younger workers, and thus smaller apparent penalties and premia if we restrict the samples in Tables 3–5 to workers ages 18–30. In fact, all beauty premia and penalties in the QES are larger in this subsample than in the basic estimates in Table 3. In the other two samples half the estimates increase in absolute value, half decrease. There is no evidence of a weaker relation between earnings and beauty among younger workers.

Another possible explanation for our findings is a possible tendency for greater attractiveness and higher earnings in adulthood to be joint products of a priviliged family background. Only the QAL contained variables (e.g. father's occupation) that allowed us to attempt to control for such effects. If family background in general were important, one would expect these partial indicators of it to have a noticeable effect on the estimates. They do not, suggesting that the unobservable background measures are unlikely to be biasing our results seriously.[15]

These three pieces of evidence reinforce the conclusion that, whatever the causes, people who are better–looking receive higher pay, while bad–looking people earn less than average, other things equal. It is crucial to stress that these penalties and premia reflect the effects of beauty in all its aspects, not merely one of its many components such as height, weight, complexion, facial structure, etc.

VI. The Absence of Differences by Gender

Particularly surprising in light of some popular discussion (e.g., Wolf, 1991) is the absence of significantly larger penalties and premia, especially the latter, for women than for men. If anything, the evidence goes in the opposite direction: Men's looks may have bigger effects on their earnings than do women's. One simple explanation might be that our results are a statistical artifact produced because the beauty ratings are a noisier signal of women's physical appearance than of men's. The evidence contradicts this: In the longitudinal part of the QOL the beauty ratings of women are slightly <u>less</u> variable over the three years than those of men.

One way that beauty can affect women's labor–market success is by influencing their labor–force participation. To examine this possibility we estimate standard labor–force participation probits that include the measures of attractiveness. These are estimated for married women (the overwhelming majority of the samples) for both the QAL and the QOL, and for the longitudinal subsample of the QOL.

The coefficients on the beauty measures included in these probits are shown in the first four columns of Table 7. The t–statistics on the above–average looks rating are tiny and the coefficients are always nearly zero. There is little evidence that good–looking women are more likely to be in the labor force than otherwise identical women. Though the estimates from the QAL are not significantly nonzero, the effects of below–average looks on women's participation are negative in that sample; and in the QOL these effects are significantly negative. They also are not small. For example, the 6 percent of married women with below–average looks are 8 percent less likely to partipate than average–looking women.[16]

There is thus some evidence that women select themselves out of the labor force if they are particularly unattractive. This selectivity, though, has no important impact on the basic estimates of the effects of looks on earnings (in columns (5) of Tables 4 and 5). Correcting for selectivity in the QAL changes the estimated premium associated with above-average looks from .128 to .130. Accounting for this form of selectivity does not alter the premium in the QOL and changes the earnings penalty from −.058 to −.036.

Another possibility is that looks affect women's economic success by altering their opportunities for marriage. Holding constant a woman's age and educational attainment, in all three samples her physical appearance is completely unrelated to her likelihood of being married. It does, though, affect the quality of the husband whom she marries. We use data on husband's education in the QES to estimate ordered probits that include our standard pair of measures of physical appearance of the married woman (and also her health, her husband's age and her education, to account for assortive mating). The results, presented in column (5) of Table 7, also show that above-average looks have essentially no effect on the outcome, in this case on the quality of the husband to whom the woman is matched. However, all else equal below-average looking women marry men whose educational attainment is less than what the women's own educational attainment predicts.[17] Women face an additional economic penalty for bad looks in the form of marriage to husbands whose potential earnings ability is less.

The results show that the economic penalties facing below-average looking women are not limited to hourly earnings. Both their success in the marriage market and their likelihood of working outside the home are reduced by their bad looks. No such effects exist for below-average looking men; and there is no apparent premium in the marriage market or extra effect on participation for either good-looking women or men.

VII. Sorting, Productivity or Discrimination?

Having demonstrated that the labor market does reward beauty, we now consider the sources of the penalties and premia. The model presented in Section III demonstrated that it is difficult to disentangle the effects of customer discrimination/productivity differences and the sorting they induce from the effects of employer discrimination. It suggested that to examine these issues we need to learn how workers are sorted into occupations and to discover how the earnings regressions of Tables 3–5 are affected if the beauty measures are interacted with measures of the possible importance of beauty in the occupation.

A test for sorting requires prior determination of the occupations where looks are likely to enhance productivity. In the absence of a widely accepted objective measure for determining this, we use three independent subjective methods. The first is based on the Dictionary of Occupational Titles (DOT) (U.S. Department of Labor, 1977). We assign each worker to a DOT occupation using three–digit occupational codes in both the QES and the QAL and note the DOT measure of "the job's relationship to people". Since physical attractiveness can affect productivity through the worker's interactions with customers or coworkers, we classify jobs with DOT measures that suggest an important role for interpersonal communication as ones in which looks are important.[18]

The second method relies on the opinions of eight adults with at least one year of full–time labor–market experience who were asked to rate each of the three–digit occupations on a three–point scale: 0, looks are probably not important; 1, looks might be important; and 2, looks are definitely important.[19] If the average rating of the occupation exceeded .5, we treat looks as being important in the occupation and form a dummy variable reflecting this average of the subjective ratings.

The third measure uses the survey (Holzer, 1993) in which employers were asked if an applicant's appearance was an important consideration in filling the most recent job vacancy. The occupational category of the vacancy was also recorded, as was the gender of the applicant hired. We first divided the survey data on the basis of the gender of the worker hired, then compiled for each gender a list of occupations that seemed fairly homogeneous with respect to the importance of appearance and for which there were at least ten observations. Next we calculated for each occupation/gender cell the percentage of employers responding that appearance was very important or somewhat important and matched these cell percentages where possible to workers from the QES and the QAL.[20]

The Appendix Table lists the occupational categories chosen from the employer survey data, along with the cell sizes and percentages of employers responding that appearance was important. For men we define an occupation as one with "looks important" if more than 40 percent of the employers responded that appearance was important; for women, the dividing line is 44 percent. The Appendix Table shows that occupations with higher percentages are generally those with more contact between the worker and the firm's customers.

If workers sort themselves among occupations/employers based in part on the relative productivity of their beauty, we would observe the highest average rating of individuals' looks in those occupations where our indexes suggest looks matter most. Table 8 presents the fractions of workers in each of the three categories of individuals' looks who work in occupations where looks are important. With three rating schemes for the occupations, two samples and both genders we have constructed twelve tests for occupational sorting. Formal tests for sorting yield significant χ^2-statistics in only four of the twelve rows. A good way to summarize the results is that all three rating schemes yield a significant relationship between our measures of the importance of beauty in an occupation and the beauty of workers in that occupation in the QAL but not in the QES. But in seven of the twelve rows the percentage of workers in jobs where looks are important is monotonically increasing as one moves up the scale of individuals' looks. More important, in ten of them above-average looking people are most likely to work in occupations where looks are important.

The results in Table 8 provide some weak evidence of sorting across occupations by beauty. Whether the weakness of the evidence is due to imperfections in our proxies for differences in the importance of beauty among occupations or to the relatively minor role that sorting by beauty plays is unclear. Taken at face value, though, the results give some support to the idea that the effects of beauty on earnings that we demonstrated in Section V are at least partly associated with sorting.

As discussed in Section III, it is worth knowing the extent to which the earnings differential is a function of some feature of the occupation rather than the appearance of the individual. To examine this issue we augment the earnings regressions of Tables 3–5 with dummy variables signifying whether or not looks are important in an occupation and with interactions between these variables and the individual's own looks. The occupational-crowding model would lead one to expect more of the looks differential to be captured by the occupation variables, while productivity/customer discrimination or pure employer-discrimination would lead these terms to have little effect.

The results of this test are shown in Table 9, which presents equations analogous to those in columns (1) and (4) of Table 3 (columns (1) and (5) of Table 4). For the DOT and subjective measures the samples are identical to those used in Tables 3 and 4. The coefficients on the main effects representing the respondents' own beauty are not greatly different from what they were in those tables; and the p-values on the F-statistics testing the pair of variables also differ little from the corresponding estimates in those tables.

Even holding constant occupational beauty, below–average looking workers receive substantial penalties (except, as before, for women in the QAL) and above–average looking workers receive earnings premia (especially women in the QAL). In the samples using the employer–based estimates of occupational looks, which contain roughly 40 percent fewer observations, the effects of the workers' own looks are significant at least at a low level in three of the four cases.

The main effects of occupational looks exceed their standard errors in six of the twelve equations. The $\bar{R}^2$ here are higher for the QES men, lower for the QES women, and higher in one case, lower in the other for both QAL samples than in Tables 3 and 4, while in the reduced samples using the employer–based indexes the $\bar{R}^2$ are increased in three of the four cases.[21] Taken together, the estimates provide a hint that occupational requirements for beauty may produce independent effects on earnings; but we cannot reject the possibility that they have no effect.

This exercise demonstrates one thing very clearly: The effects of an individual's own looks on his or her earnings are very robust. That there are earnings premia and penalties for looks independent of occupation suggests that occupational crowding along the dimension of looks is not the chief cause of those premia and penalties. That there is some evidence of sorting implies that pure employer discrimination does not alone describe the role of beauty in the labor market. Tables 8 and 9 suggest that at least part of the explanation for the apparent impact of individuals' looks on their earnings is that beauty is productive, arising perhaps from the effects of customers' preferences, and/or that pure employer discrimination on the basis of looks exists. We cannot, though, determine how much of the total effect stems from these two possible sources.

VIII. Conclusions and Implications

In empirical analyses based on three distinct sets of household data we have discovered a number of facts about beauty in the labor market. Other things equal, the wages of people with below-average looks are lower than those of average-looking workers; and there is a premium in wages for good-looking people that is slightly smaller than this penalty. The penalty and premium may be higher for men, but these gender differences are not large. There is some evidence that the labor market sorts the best-looking people into occupations where their looks are productive.

It is difficult to disentangle the effects of alternative sources of earnings differentials in the data. Nonetheless, our finding that individuals receive earnings penalties and premia even after we account for their occupations suggests that occupational crowding does not explain how beauty affects the labor market. Other explanations, such as inherent productivity differences, the possibe effects of customer discrimination, or taste-based employer/employee discrimination seem to provide better explanations.[22] More light could be shed on these questions by examinations of the relationship between looks and earnings within particular narrowly-defined occupations.

That there is a payoff in the labor market for good looks and a penalty for bad looks should be obvious without our demonstration: Why else would workers spend time on grooming before going to work; and why would they spend money on clothing and other items designed to enhance their appearance at work? What our demonstration shows is the magnitude of the incentives to expend these resources and the mechanisms by which they might arise. The results lead naturally to studying other issues in discrimination along various dimensions, such as physical and mental handicaps. In each case the method we have developed to aid distinguishing between productivity/discrimination and occupational sorting can be applied mutatis mutandis to discover the source of other apparently discriminatory outcomes.

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FOOTNOTES

1. Examples of each are Blau and Beller (1992); Borjas and Tienda (1985); Bloom and Grenier (1992), and Fechter and Thorpe (1978).

2. Quoted by Fred Siegel, "The Cult of Multiculturalism," New Republic, February 18, 1991, p. 38, from an official document from Smith College. The legislation was proposed in the Philippine Congress, reported by the Associated Press, December 13, 1992. The case law and the ADA are discussed by McAdams et al (1992). A recent case is Hodgdon v. Mt. Mansfield Company, November 6, 1992, in which the Vermont Supreme Court ruled that a chambermaid's lack of upper teeth qualified as a handicap protected under the state's Fair Employment Practices Act.

3. Given the distributions across the five categories only 75 percent would be so classified randomly. While 35 percent are classified identically in all three years, only 22 percent would be categorized this way randomly.

4. An unpublished work in the late 1970s by Robert Frank of Cornell University correlated earnings of recent Cornell graduates with ratings of their appearance (from pictures) by a group of current undergraduates.

5. This potential omitted-variable problem is distinct from the problem of unobserved productivity that is correlated with attractiveness. In addition to biasing attempts to estimate a looks differential, the latter correlation could be the basis for a sort of statistical discrimination, in which attractiveness was used by employers as a noisy signal of some other productivity factor.

6. These are the only broadly-based surveys we could find that contain such information. A number of other surveys, including one interesting proprietary data set used in a (racial) discrimination case by Mark Killingsworth, contain information on the worker's general appearance. This latter is more likely to be influenced by income than the physical appearance measures that are available in our samples.

7. All the equations were recomputed using annual earnings, with weekly hours included as an independent variable. None of our conclusions is changed qualitatively by this modification.

8. Note that in 1971 in the U.S. the minimum wage was $1.60 per hour and in 1977 was $2.30. In Canada in 1981 the federal minimum was $3.50, and some provincial minima were even higher. The disqualifications on the wage rate are thus designed to exclude those observations for which measurement errors are likely. Excluding the small fraction of workers whose estimated hourly wage is far below statutory minima does not imply any selectivity on a characteristic that is correlated with looks. In the QAL, for example, there is no relation at even the 20 percent level of significance between the beauty measures and the probability of exclusion from the sample for this reason. Even if there were, the fraction of people so excluded is below 5 percent of the sample.

9. Of the respondents in the QES between the ages of 18 and 64 this disqualified 10; from the QAL, 126; and from the QOL, 18.

10. One related possibility is that interviewers of different sexes rate the respondents differently. This possibility is also handled by the estimates using interviewer fixed effects. It is not likely to be a problem in any case, since 95 percent of the respondents in the two American samples were interviewed by women. A related problem is that there may be differences in the interviewers' ability to classify workers of different races. Unsurprisingly, given that the overwhelming majority of the respondents are white, the estimates in Tables 3 and 4 change only minutely when African–Americans are deleted from the sample.

11. The rating scale for weight (in descending order) was: "Obese;" "overweight;" "average for height;" "underweight," and "skinny." Among women (men) 3.2 (.7) percent were rated obese; 19.6 (17.4) percent were rated overweight; 65.8 (72.7) percent were considered average; 11.2 (8.5) percent were rated underweight, and .2 (.7) percent were rated skinny.

12. The expectations are of a doubly–truncated normal density and are calculated based on Johnson and Kotz (1970).

13. If the pair of dummy variables used in columns (2) and (6) is included instead here, the $\bar{R}^2$ are slightly lower, .283 for men and .408 for women.

14. Remember that hourly earnings were calculated using actual weekly hours, but assuming that all workers spent the same number of weeks employed. The QES and QOL provide data on weeks of layoff in the last year in the QES (two years in the QOL). Tobit estimates of the determinants of weeks of layoff (for the roughly 7 percent of males who reported having been laid off) were produced and included controls for education level, experience, union status, tenure with the firm, and firm or establishment size. In both samples the t–statistics on the dummy variable for above–average looks were below .5 in absolute value. Bad looks raised the probability of layoff and lengthened its duration, with t–statistics of 1.54 in the QES (1.40 in the QOL). The conclusion that there is only weak asymmetry in the effect of looks on hourly earnings becomes a bit stronger when we consider effects on weeks of involuntary unemployment.

15. We are indebted to Bob Willis for suggesting this point.

16. Not surprisingly, similar probits on men's labor–force participation yielded no relationship between looks and the probability of participation.

17. The same ordered probits estimated for the education of wives of married men in the QES generated very small coefficients on the beauty variables, with t–statistics below .3 in absolute value.

18. We rely on the fifth digit of the DOT code, which can take nine different values according to whether the job involves "mentoring," "negotiating," "instructing," "supervising," "diverting," "persuading," "speaking, signaling," "serving," or "taking instructions, helping." We treat all but the last as indications that interpersonal interaction is an important aspect of the occupation.

19. The 28 pairwise correlations of the ratings of the 504 occupations ranged from .36 to .61, with a mean of .47.

20. The survey targeted employers of low–education workers. This produced too few observations in several broad occupation cells to calculate occupational beauty ratings, preventing many QES and QAL sample members from being included in this part of the analysis.

21. A more straightforward test simply includes a vector of dummy variables for one–digit occupations in the basic equation for both samples and sexes. (Finer detail is not possible given some of the cell sizes.) The coefficients on the dummy variables for below– and above–average looks are hardly altered in size or significance. Among the QES men (women), the coefficients (analogous to those in columns (1) and (4) of Table 3) become –.156 and .014 (–.100 and .026). Among the QAL men (women), the coefficients (analogous to those in columns (1) and (5) of Table 4) become –.059 and .062 (.068 and .115).

22. Another possibility (alluded to in footnote 5) is that attractiveness is a signal of otherwise unobservable (to the employer) productivity. If this were so, and employers learned about workers' productivity as they acquire tenure, the impact of looks would diminish as tenure increases. Reestimates of the basic equations in Tables 3 and 5 for the QES (QOL) based on workers with at least three (five) years of tenure with the firm refute this possibility. Of the eight coefficients on physical appearance four are larger in absolute value, four smaller, and the only change greater than one standard error is the <u>higher</u> penalty for below–average looking senior men in the QOL.

Table 1. Ratings of Beauty, Canadian Quality of Life, 1977, 1979, 1981

Transition Matrices, 1977-79, 1979-81 Combined

MEN (N = 1504)

First Year		Second Year 1	2	3	4	5
Strikingly handsome	1	0.2	0.9	1.0	0.0	0.0
Above average (good looking)	2	1.4	14.9	15.9	0.7	0.0
Average	3	0.9	15.1	37.5	4.8	0.1
Below average (plain)	4	0.1	0.4	4.0	1.7	0.1
Homely	5	0.0	0.1	0.1	0.1	0.1

1977–79: $\chi^2(16) = 151.78$; 1979–81: $\chi^2(16) = 142.67$.

WOMEN (N = 2147)

		1	2	3	4	5
Strikingly handsome	1	0.4	1.4	0.6	0.0	0.0
Above average (good looking)	2	1.0	14.3	15.8	1.0	0.0
Average	3	0.7	13.3	37.0	4.3	0.4
Below average (plain)	4	0.0	0.8	6.2	2.0	0.2
Homely	5	0.0	0.1	0.2	0.2	0.1

1977–79: $\chi^2(16) = 231.13$; 1979–81: $\chi^2(16) = 169.17$.

Summary of Three-year Transition Matrix

BOTH GENDERS (N = 1330)

Absolute Deviations from 1977 Rating

1977 Rating	0,0	0,1	1,1		0,2	1,2	2,2		2,3
			(same)				(same)		
Strikingly handsome	0.1	0.2	0.8	0.0	0.1	1.1	0.2	0.0	0.1
Above average	8.1	13.2	10.4	0.6	0.6	0.9	0.2	0.0	0.0
Average	26.3	19.7	6.8	1.0	0.7	0.4	0.1	0.0	0.0
Below average	0.3	2.9	3.8	0.2	0.2	0.8	0.2	0.0	0.1
Homely	0.0	0.1	0.2	0.0	0.0	0.1	0.2	0.0	0.0
TOTAL	34.8	36.0	21.9	1.7	1.5	3.2	0.7	0.0	0.2

Table 2. Distribution of Looks: Quality of Employment Survey, 1977; Quality of American Life, 1971; Canadian Quality of Life, 1977, 1979, 1981 (percent distributions)

	Quality of Employment Survey		Quality of American Life		Canadian Quality of Life (Pooled)	
CATEGORY	Men	Women	Men	Women	Men	Women
Strikingly beautiful or handsome	1.4	2.1	2.9	2.9	2.5	2.5
Above average for age (good looking)	26.5	30.4	24.2	28.1	32.0	31.7
Average for age	59.7	52.1	60.4	51.5	57.9	56.8
Below average for age (quite plain)	11.4	13.7	10.8	15.2	7.2	8.3
Homely	1.0	1.7	1.7	2.3	0.4	0.7
N =	959	539	864	1194	3804	5464

Table 3. The Impact of Looks on Employees' Earnings, QES 1977
(Dependent Variable is log(Hourly Earnings))[a]

VARIABLE	(1)	(2)	(3)	(4)	(5)	(6)
		Men			Women	
Looks:						
Below average	−.164 (.046)		−.162 (.046)	−.124 (.066)		−.107 (.071)
Homely		−.239 (.144)			−.371 (.199)	
Plain		−.156 (.048)			−.098 (.069)	
Average	——	——	——	——	——	——
Above average	.016 (.033)		.010 (.034)	.039 (.048)		.035 (.049)
Good looking		.011 (.034)			.049 (.048)	
Handsome or beautiful		.136 (.135)			−.120 (.158)	
Obese			.119 (.172)			−.122 (.134)
Overweight			−.024 (.038)			−.016 (.058)
Tall			.027 (.045)			.104 (.114)
Short			−.105 (.060)			−.017 (.124)
$\bar{R}^2$	.403	.403	.404	.330	.332	.327
p on F-statistic for Beauty Variables	.001	.004	.001	.069	.084	.173
N =		700			409	

[a]Standard errors are in parentheses here and in Tables 4–7 and 9. The equations here also include continuous and indicator variables measuring actual experience (and its square), union membership, health status, marital status, race, years of vocational school and region, and vectors of indicator variables for educational attainment, tenure with the firm, firm size, city size and industry. The regressions exclude observations for which data were not available to form these measures, and for which weekly hours worked < 20, hourly earnings < $1, and age > 64 or age < 18.

Table 4. The Impact of Looks on Employees' Earnings, QAL 1971 (Dependent Variable is log(Hourly Earnings))[a]

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
	Men				Women			
VARIABLE								
Looks:								
Below average	−.078 (.069)	−.138 (.081)		−.079 (.069)	.069 (.073)	.122 (.095)		.061 (.073)
Homely			−.238 (.192)				−.355 (.250)	
Plain			−.058 (.072)				.097 (.075)	
Average	——	——	——	——	——	——	——	——
Above average	.065 (.045)	.109 (.052)		.064 (.045)	.128 (.056)	.129 (.076)		.118 (.056)
Good looking			.072 (.046)				.122 (.057)	
Handsome or beautiful			.006 (.111)				.249 (.149)	
Short				.095 (.101)				.235 (.109)
Tall				.018 (.066)				.251 (.214)
Interviewer Effects	No	Yes	No	No	No	Yes	No	No
$\bar{R}^2$	.371	.471	.370	.370	.283	.332	.288	.293
p on F-statistic for Beauty Variables	.124	.014	.258	.130	.072	.174	.060	.108
N =	476				307			

[a]Also included are continuous and indicator variables measuring experience (age − education − 6) and its square, health status, race, marital status and region, and vectors of indicator variables measuring educational attainment, city size, immigrant status of the individual, his or her parents and grandparents, father's occupational status, and industry. The regressions exclude observations for which data were not available to form these measures, and for which weekly hours worked < 20, hourly earnings < $.75, and age > 64 or age < 18.

Table 5. The Impact of Looks on Employees' Earnings, Canadian QOL 1981 (Dependent Variable is log(Hourly Earnings))[a]

VARIABLE	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
	Men				Women			
Looks:								
Below average	−.012 (.052)	−.027 (.054)			−.058 (.063)	−.072 (.067)		
Average	——	——			——	——		
Above average	.073 (.028)	.059 (.030)			.013 (.027)	.010 (.029)		
$\hat{B}_{1981}$			.033 (.188)				−.025 (.247)	
$\hat{B}^2_{1981}$			−.018 (.035)				.0007 (.047)	
B^*				.218 (.077)				.068 (.075)
B^{*2}				−.082 (.039)				−.011 (.040)
Interviewer Effects	No	Yes	No	No	No	Yes	No	No
$\bar{R}^2$	.302	.306	.285	.295	.394	.389	.410	.412
p on F-statistic for Beauty Variables	.023	.099	.135	.012	.540	.492	.845	.320
N =	887	887	358	358	883	883	335	335

[a]Also included are continuous and indicator variables measuring actual experience and its square, health, union and marital status, and non-English speaker, and vectors of indicator variables measuring educational attainment, tenure with the firm, firm size, region and industry. The regressions exclude observations for which data were unavailable to form these measures and for which weekly hours worked < 20, hourly earnings < \$1, and age > 64 or age < 18.

Table 6. Pooled Estimates of the Impact of Looks on Hourly Earnings

	Penalty for Below-average Looks	Premium for Above-average Looks	p on F-statistic for Beauty	p on Inter-sample Equality of Beauty Effects
Men:				
All three samples	-.091 (.031)	.053 (.019)	.0001	.246
Two U.S. samples	-.132 (.039)	.036 (.027)	.0003	.443
Women:				
All three samples	-.054 (.038)	.038 (.022)	.042	.163
Two U.S. samples	-.042 (.049)	.075 (.037)	.041	.123
Men and Women Combined:				
All three samples	-.072 (.024)	.048 (.015)	.0001	.106
Two U.S. samples	-.092 (.031)	.046 (.022)	.0002	.051

Table 7. The Impact of Looks on Married Women's Labor-Force Participation, QAL 1977, QOL 1981, and on Husband's Education, QES 1977[a]

	(1)	(2)	(3)	(4)	(5)
	Probits on Participation				Ordered Probit on Education
	QAL		QOL		QES
VARIABLE					
Looks:					
Below average	−.168 (.176)	−.310 (.153)	−.468 (.239)		−.510 (.232)
Average	——	——	——		——
Above average	−.034 (.131)	−.010 (.078)	.014 (.113)		−.001 (.184)
B^*				.310 (.157)	
B^{*2}				−.127 (.090)	
Pseudo-R^2	.148	.067	.084	.084	.183
N =	583	1287	621	621	199

[a]In the QAL the dependent variable equals one if the women was employed at the time of the interview. In the QOL it is whether she stated she was in the labor force on the interview date. Also included in the probits in both samples are continuous and indicator variables measuring experience (and its square) and indicator variables for educational attainment, health status, age and the presence and ages of children of children. In the probits based on the QAL an indicator variable for race is included, as is a measure of family income less the woman's income. In the ordered probits husband's education is divided into four categories (less than 12 year, 12 years, 13 through 15, and 16 years and up), and his age and indicator variables for the wife's educational attainment and health status are included.

Table 8. Occupational Sorting: Percentage of Sample in Occupations with Looks Important

Looks Are Important	Own Looks: Below average	Average	Above average	Total	χ^2	N
		QES				
(Rating of Looks):		Men				
DOT	62.6	63.5	64.7	63.7	0.14	700
Subjective	13.2	13.3	11.1	12.7	0.65	700
Employer	46.5	52.2	44.3	49.3	2.14	428
		Women				
DOT	76.4	76.2	80.9	77.8	1.16	409
Subjective	21.8	26.2	28.7	26.4	0.96	409
Employer	45.9	45.2	47.1	45.9	0.10	309
		QAL				
		Men				
DOT	40.0	55.6	64.5	56.9	9.00	476
Subjective	17.8	12.9	22.4	16.4	6.50	476
Employer	33.3	61.2	63.3	59.3	7.48	268
		Women				
DOT	67.4	73.9	81.1	75.6	3.61	307
Subjective	34.9	35.3	40.5	37.1	0.87	307
Employer	44.1	44.5	62.6	51.1	8.30	270

$\chi^2_{.95}(2) = 5.99$
$\chi^2_{.90}(2) = 4.60$

Table 9. Sorting, Looks and the Determination of Earnings, QES, 1977, QAL 1971; (Dependent Variable is log(Hourly Earnings))[a]

Looks:	Below average	Below x Occupation index	Above average	Above x Occupation index	Occupation index	$\bar{R}^2$	p on F-statistic on Main Effects
SAMPLE AND OCCUPATIONAL INDEX							
QES Men:							
DOT	-.177	-.036	.041	.072	.052	.405	.002
	(.058)	(.095)	(.042)	(.069)	(.041)		
Subjective	-.162	.007	.012	.051	.124	.405	.003
	(.049)	(.127)	(.035)	(.097)	(.072)		
Employers	-.187	-.112	-.095	.103	-.066	.410	.026
	(.076)	(.107)	(.057)	(.084)	(.049)		
QES Women:							
DOT	-.174	-.218	.023	-.068	.032	.329	.036
	(.075)	(.157)	(.054)	(.119)	(.085)		
Subjective	-.115	-.037	.050	-.036	.083	.326	.130
	(.074)	(.151)	(.055)	(.096)	(.093)		
Employers	-.078	-.013	.152	-.312	.216	.315	.064
	(.107)	(.158)	(.076)	(.111)	(.077)		
QAL Men:							
DOT	-.102	-.057	.070	.011	.093	.373	.224
	(.107)	(.142)	(.056)	(.089)	(.055)		
Subjective	-.097	.078	.045	.089	.085	.371	.223
	(.076)	(.177)	(.048)	(.099)	(.102)		
Employers	.145	-.107	.124	-.072	-.006	.213	.449
	(.150)	(.250)	(.121)	(.152)	(.095)		
QAL Women:							
DOT	.049	-.056	.166	.175	-.066	.282	.031
	(.088)	(.159)	(.063)	(.130)	(.088)		
Subjective	.130	-.172	.075	.142	-.053	.287	.266
	(.090)	(.152)	(.068)	(.099)	(.099)		
Employers	.253	-.304	.261	-.355	.218	.272	.058
	(.153)	(.229)	(.127)	(.162)	(.117)		

[a]Each regression includes the same additional variables as in the corresponding regression in Table 3 or 4. Those using the occupational indexes based on the DOT and subjective measures also use the same samples. Those using the survey of employers use smaller samples, N = 428, 309, 265 and 259.

Appendix Table. Occupational Categories Taken from Employer Survey

MEN

Occupation	Percent of Employers Saying Looks Very or Somewhat Important	Cell Size
Precision Production	16.6	24
Machine Operators and Tenders	25.0	24
Protective Services	30.8	13
Construction	33.4	15
Handlers, Equipment Cleaners, and Laborers exc. Misc.	38.9	36
Cleaning and Building Service Workers	40.0	15
Technologists and Technicians, ex. Health	46.2	17
Administrative Support and Clerical Occupations, ex. Mailroom and Record Clerks	46.6	15
Mechanics and Helpers, ex. Auto.	46.9	32
Mailroom Workers, Record Clerks	47.1	17
Heavy Truck and Trailer Drivers	49.9	12
Drivers of Light Delivery Trucks, Taxis, or Buses	55.0	20
Fabricators, Assemblers, Hand Workers	60.2	15
Auto Mechanics	66.7	12
Food Preparation Occups.	66.7	12
Sales Occupations, Commodities ex. Retail	70.0	10
Retail Sales Occupations	90.9	22

Appendix Table, cont.

	WOMEN	
Registered Nurses, Phys. Assts.	18.2	11
Machine Operators and Tenders	22.2	18
Office Workers I: Information, Correspondence,and Record Clerks; Other General Office Occups ex. Secretaries, Receptionists	37.1	37
Cleaning, Building Service Workers	38.9	18
Office Workers II: Office Machine and Communications Operators; Mailroom, Material Recording, and other Misc. Clerks; Adjusters and Investigators.	40.0	30
Office Workers III: Financial Record Processing	42.3	26
Dental, Nursing, or Health Aides	42.9	14
Food Preparation Occups.	43.8	16
Teachers, K-12	57.1	14
Secretaries, Stenographers, Typists	59.6	52
Dental Hygienists, LPNs, Misc. Health Technicians	61.1	18
Retail Sales and Counter Clerks	63.7	11
Bank Tellers	65.0	20
Retail Salespeople	65.2	23
Personal Service Occups.: Mostly Cosmetologists, Ushers and Attendants	71.4	14
Cashiers	78.6	28
Receptionists	81.5	
Waitresses and Food Counter Workers	81.8	22