Why Beauty Matters

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Abstract

We decompose the beauty premium in an experimental labor market where 'employers' determine wages of 'workers' who perform a maze-solving task. This task requires a true skill which we show to be unaffected by physical attractiveness. We find a sizable beauty premium and can identify three transmission channels. (1) Physically-attractive workers are more confident and higher confidence increases wages. (2) For a given level of confidence, physically-attractive workers are (wrongly) considered more able by employers. (3) Controlling for worker confidence, physically-attractive workers have oral skills (such as communication and social skills) that raise their wages when they interact with employers. Our methodology can be adopted to study the sources of discriminatory pay differentials in other settings.

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1 Introduction

In their seminal work, Hamermesh and Biddle (1994) found that physically-attractive workers derive sizable rents from their looks. Workers of above average beauty earn about 10 to 15 percent more than workers of below average beauty. The size of this *beauty premium* is economically significant and comparable to the race and gender gaps in the US labor market.

In this paper we decompose the beauty premium that arises during the wage negotiation process between employer and worker in an experimental labor market. We let workers perform a task that requires a true skill which is uncorrelated with physical attractiveness. This allows us to abstract away from the productivity enhancing effects of beauty (Biddle and Hamermesh, 1998; Pfann, Bosman, Biddle, and Hamermesh, 2000). Although these effects are important in some occupations with a lot of customer and co-worker interaction they do not seem to explain the bulk of the overall beauty premium. Hamermesh and Biddle (1994) find that accounting for the intensity of job-related interaction has almost no effect on the cross-sectional beauty premium.

The participants in our experiment are undergraduate and graduate students from Tucuman, Argentina who are divided into groups of 'workers' and 'employers'. Workers are paid to solve as many computer mazes as possible during a 15 minute employment period. Employers estimate the productivity of workers and set wages accordingly. We vary the degree of visual and oral interaction between workers and employers in order to decompose the beauty premium. We also measure workers' confidence by asking them for an estimate of their future productivity after they have solved a practice maze.

We can identify three channels through which physical attractiveness raises an employer's estimate of a worker's ability: the *confidence* channel and the *visual and oral stereotype* channels. The confidence channel operates through *workers' beliefs*: we show that physically-attractive workers are substantially more confident and worker confidence in return increases wages under oral interaction. The two stereotype channels affect *employers' beliefs*: employers (wrongly) expect good-looking workers to perform better than their less attractive counterparts under both visual and oral interaction even after controlling for individual worker characteristics and worker confidence.

The advantage of our experimental approach is that we can open the 'black box' of the wage negotiation process between worker and employer. A large body of work in social psychology suggests that factors such as confidence and physical attractiveness play a big role in labor market outcomes. Beauty is perceived to be correlated with intelligence, social skills and health (Feingold, 1992; Eagly, Ashmore, Makhijani, and Longo, 2001).[1] According to the *kernel of truth hypothesis* the physical attractiveness stereotype can become a self-fulfilling prophecy: teachers expect better looking kids to outperform in school and devote more attention to children who are perceived to have greater potential (Hatfield and Sprecher, 1986). Preferential treatment in return builds confidence as well as social and communication skills.

Recent research in labor economics has emphasized the importance of non-cognitive skills such as confidence for labor market success and the role of physical attributes in acquiring these skills. Evidence from early childhood intervention programs such as the Perry preschool program demonstrates that these programs raise lifetime earnings by improving students' social skills and motivation rather than through gains in cognitive abilities which are short-lived and dissipate over time (see Heckman (2000)). The abundant popular self-help literature on 'positive thinking' provides overwhelming anecdotal evidence that people recognize the income-enhancing effects of confidence.[2] Persico, Postlewaite, and Silverman (2003) analyze the well-known height premium and find that teenage height rather than adult height boosts income: this suggests that height promotes the acquisition of non-cognitive social skills such as confidence which in turn increase wages.

The use of an experimental framework to decompose the beauty premium is novel to the best of our knowledge. Notable experimental papers on the effects of beauty in non-labor market settings are Solnick and Schweitzer (1999) on the ultimatum game, Mulford, Orbell, Shatto, and Stockard (1998) and Kahn, Hottes, and Davis (1971) on the Prisoner's Dilemma, Andreoni and Petrie (2004) on public goods games and Eckel and Wilson (2004) on trust games.

The balance of the paper is organized as follows. Section 2 presents a simple theoretical framework to organize our analysis. Section 3 describes the design of the experiment and our empirical strategy and section 4 discusses our experimental data. Section 5 shows that beauty has no productivity enhancing effects for solving mazes but nevertheless increases the earnings of workers. In section 6 we identify the various channels through which beauty raises workers' wages in our experiment.

[1] Consistent with our findings, there is no correlation between beauty and cognitive ability (Feingold, 1992).

[2] Parents are continuously reminded to use positive reinforcement in interactions with their children in order to build self-esteem and instill confidence in them. Team sports and group activities are encouraged not just because students benefit from physical activity but because they can enhance self-esteem.

Section 7 concludes.

2 Theoretical Framework

The employer has to form an estimate about the productivity A of a worker which is a function of an observable resume variable x and an unobservable component $\eta \sim N\left(0, \sigma_\eta^2\right)$:

$$A = \alpha x + \eta \tag{1}$$

The worker receives a signal C of his own productivity which we call his *confidence*:

$$C = \eta + \pi B + \epsilon_C \quad \epsilon_C \sim N\left(0, \sigma_C^2\right) \tag{2}$$

The term πB captures any bias of the worker's confidence arising from his physical attractiveness B. We ignore this term for now ($\pi = 0$).

Two indicator variables T_O and T_V describe whether worker and employer can communicate orally or visually.[3] Under oral communication the employer can observe an unbiased signal $\tilde{C}$ of the worker's confidence:

$$\tilde{C} = C + \epsilon_{\tilde{C}} = \eta + \pi B + (\epsilon_C + \epsilon_{\tilde{C}}) \quad \epsilon_{\tilde{C}} \sim N\left(0, \sigma_{\tilde{C}}^2\right), B \sim N\left(0, \sigma_B^2\right) \tag{3}$$

The employer's can use this signal to improve her estimate of the worker's productivity:

$$w^* = \alpha x + \delta T_O * \tilde{C} \quad \text{where } \delta = \frac{\sigma_\eta^2}{\sigma_\eta^2 + \pi^2 \sigma_B^2 + \sigma_C^2 + \sigma_{\tilde{C}}^2} \tag{4}$$

The employer will put a positive weight on the worker's signal $\tilde{C}$ unless the worker perfectly conceals his private information.[4]

The employer's *actual* estimate $\hat{w}$ is subject to two stereotype biases that arise from a worker's physical attractiveness B and the his communication and social skills S which are also a function of beauty:

$$\begin{aligned} \hat{w} &= w^* + \beta_V T_V * B + \beta_O T_O * S \\ S &= B + \epsilon_S \quad \text{where } \epsilon_S \sim N\left(0, \sigma_{\epsilon_S}^2\right) \end{aligned} \tag{5}$$

[3] If an interview is conducted only over the telephone we have $T_O = 1$, $T_V = 0$ while in a face to face conversation $T_O = 1$ and $T_V = 1$.

[4] Human resource officers are trained to extract job-relevant information from job interviews. In our regressions we also include an interaction term between oral communication T_V and confidence to test whether more confident workers can increase their wages by 'looking' more confident.

The coefficient β_V captures the *visual stereotype channel* which is simply the physical attractiveness stereotype from the social psychology literature. The coefficient β_O denotes the *oral stereotype channel* - physical attractiveness raises social and communication skills which in return raise an employer's estimate of the worker's productivity. We assume that the employer is unaware of these biases and hence does not correct for them.

The worker is subject to similar stereotypes as the employer and we therefore allow $\pi > 0$ in equation 2: beauty increases confidence. If the employer interacts only orally with the worker her estimate of the worker's productivity increases by $\delta\pi B$. We refer to this channel as the *confidence channel.* It is distinct from the oral stereotype channel because it operates through the worker's rather than the employer's bias.

If the employer interacts orally *and* visually with the worker and is unaware that confidence comes, in part, from beauty the same confidence channel applies. However, if she is aware that beauty boosts confidence, the employer can filter out the confidence channel and obtain a better estimate of the worker's productivity:[5]

$$w^* = \alpha x + \hat{\delta} T_O * \left(\tilde{C} - \pi B\right) \quad \text{where } \hat{\delta} = \frac{\sigma_\eta^2}{\sigma_\eta^2 + \sigma_C^2 + \sigma_{\tilde{C}}^2} > \delta \tag{6}$$

The actual wage w set by the employer is the sum of the employers' estimate $\hat{w}$ and a taste-basted discrimination component D which depends positively on a worker's physical attractiveness B:

$$w = \hat{w} + D(B) \tag{7}$$

While we will be looking for evidence of taste-based discrimination, the one shot nature of our experiment does not provide a fair testing ground to detect direct taste-based transfers which are more likely to arise in repeated interactions.

3 Experimental Design

3.1 Design

Our experimental design allows us to vary the degree of visual and oral interaction between worker and employer in order to decompose the beauty premium. Each experimental session includes 5 workers and 5 employers who are randomly assigned

[5] In subsequent empirical analysis, we do not find evidence that $\hat{\delta} > \delta$.

their roles. Employers start with an account of 4000 points while workers have no points initially.

All participants submit their basic labor market characteristics (age, sex, university, matriculation year, previous job experience, extracurricular activities and hobbies) through an online survey and have their digital photograph taken. Workers are asked to solve a practice maze of the lowest level of difficulty and their practice time is recorded[6]. The labor market characteristics of a worker together with his practice time becomes his digital 'resume'.

Each worker j is then asked for an estimate C_j of how many mazes of the next level of difficulty he expects to complete during a 15 minute 'employment period' at the end of the experiment. This information is kept secret from all other players and provides a measure of worker confidence. The worker receives a piece rate of 100 points per solved maze minus 40 points for each maze that he mispredicted when estimating C_j:

$$100 \times A_j - 40 \times |C_j - A_j| \tag{8}$$

The misprediction penalty provides the worker with an incentive to truthfully report the median of his perceived productivity distribution.[7] One implication of our experimental design is that the effective piece rate of workers is 140 points for each maze as long as they stay below their estimate and 60 points for each maze thereafter. Truthful elicitation of workers' beliefs is bound to somewhat distort incentives during the employment period. We therefore chose a generous exchange rate from points to money to ensure that even 60 points represent a salient reward.

Each worker is then matched with 5 different employers[8]. The order in which workers are matched with employers is randomized to avoid order effects. All employers see the same online resume of each worker but they differ in the mode of interaction with the worker:

B: (baseline) Employer B only sees the resume of the worker.

V: (visual) Employer V sees the resume and a frontal facial passport-like photograph of the worker.

[6] The mazes of five different levels of difficulty can be found at the Yahoo website http://games.yahoo.com/games/kidsmz.html. These mazes were first used in experimental research by Gneezy, Niederle, and Rustichini (2003).

[7] In the instructions, participants are told that at the median they are equally likely to be above their estimate as they are to fall below the estimate. We did not use a quadratic punishment scheme to reveal the expected mean of the perceived distribution because we wanted to limit the size of the maximum penalty and also keep the game as transparent as possible.

[8] In a session, each worker is matched with every employer and each employer reviews all 5 workers. This allows us to use fixed effects estimation.

O: (oral) Employer O sees the resume and conducts a free-form telephone interview with the worker of up to 5 minutes in length.

VO: (visual + oral) Employer VO sees the resume, the photograph and also conducts a telephone conversation of up to 5 minutes in length.

FTF: (face-to-face) Employer FTF sees the resume, the photograph and also conducts a face-to-face free form interview with the worker of up to 5 minutes in length[9].

The task of each employer i is to estimate the expected productivity w_{ij} of each worker j in the 15 minute employment period. Employers are provided with the same incentives as workers to truthfully reveal their estimates. Employer i faces a penalty of 40 points for each mispredicted maze of worker j. For example, if employer i decides that worker j can do 8 mazes but the worker solves 10 then the employer receives a penalty of 80 points. Therefore, the total compensation Π_i of employer i including the misprediction penalty is:

$$\Pi_i = 4000 - \sum_{j=1}^{5} 40 \times |w_{ij} - A_j| \tag{9}$$

Each employer decides on her estimates simultaneously *after* she has reviewed all five workers. We refer to employer estimates as 'wages' with the caveat that the employer does not pay those wages herself: she is only provided with incentives to assign wages equal to the median productivity of each worker.[10]

Each worker j receives five actual wages W_{ij} from the experimenter: one wage for each employer i which is calculated as follows: with probability .8, employer i's estimate is used to pay the worker $W_{ij} = 100w_{ij}$; with probability .2, the average estimate $\overline{w}$ of all employers across all workers in the session is used to set the worker's wage to $W_{ij} = 100\overline{w}$ (all draws are i.i.d. across workers and employers).

Before the employer decides on her 5 estimates but *after* she has seen all the workers, she is told which of her estimates will contribute to the worker's earnings. The exact timing of this randomization is important for our design because it allows

[9]Note that we distinguish between treatment VO (visual and oral interaction) and true face-to-face communication. Numerous studies have shown that non-verbal cues are powerful predictors of interpersonal evaluations (see Straus, Miles, and Levesque (2001) for an overview). Non-verbal signals help to form initial evaluations and cues such as eye contact amplify these first impressions (Hemsley and Doob, 1978).

[10]Our incentives are designed to simulate the incentives of a real-world perfectly competitive labor market where each employer sets wages equal to the expected productivity of each worker.

us to test for some types of direct taste-based discrimination: an employer with a taste for physical attractiveness might want to sacrifice earnings by reporting a higher estimate and incurring a larger penalty as a result. However, she has no incentive to do so if she knows that her estimate will not be used to compensate the worker. It is also crucial that an employer does not know the outcome of this randomization during the interview because she could inform the worker and hence destroy his incentives to convince the employer of his ability. It would be akin to a job interview where the worker knows in advance that he will not get the job.

After all worker-employer interactions are completed workers are taken to the computer lab for their 15 minute employment period. The total earnings Π_j of a worker j consist of his piece rate earnings minus his misprediction penalty plus all 5 wages:

$$\Pi_j = 100 \times A_j - 40 \times |C_j - A_j| + \sum_{i=1}^{5} W_{ij} \tag{10}$$

3.2 Empirical Strategy

We use the experimental data to estimate treatment-by-treatment variants of the following empirical model which is based on our theoretical framework:

$$w_{ij} = \underbrace{\alpha X_j + \alpha_P P_j}_{\text{Resume variables}} + \underbrace{\beta B_j + \delta C_j}_{\text{stereotype and confidence channels}} + \underbrace{\tau S_{ij} + \vartheta_B S_{ij} * B_j + \vartheta_C S_{ij} * C_j}_{\text{taste-based discrimination}} + \psi A_j + \zeta_i + \epsilon_{ij} \tag{11}$$

Worker j has characteristics (X_j, P_j, B_j, C_j) where X_j is a vector of all observable job market characteristics and P_j is his projected performance based on his practice time. All employers have access to the resume variables (X_j, P_j). The coefficient β and δ capture the visual/oral stereotype channels and confidence channel respectively. We define a new indicator variable S_{ij} which is equal to 1 if the employer's estimate w_{ij} determines the worker's wage ($W_{ij} = 100 \times w_{ij}$). The coefficients ϑ_O and ϑ_V are positive if there is taste-based discrimination in favor of the physically-attractive or the confident. The coefficient ψ indicates whether employers have information that improves their productivity estimate but which is not yet captured by worker characteristics (X_j, P_j, B_j, C_j). We add an error term to the specification to be able to run regressions - this error includes an employer fixed effect ζ_i and all our wage regressions are employer fixed effects regressions. Here we are exploiting the fact that each employer sets the wages of 5 different workers.

We first estimate the above specification treatment-by-treatment and later also a pooled regression to separate out our three transmission channels. Treatment B provides a consistency check because we expect both β and δ to be zero in the absence of any visual and oral interaction. Treatments V and O allow us to identify the three transmission channels. In treatment VO we can check to what extent the two stereotype effects are additive and in treatment FTF we test whether this richer interaction mode amplifies the transmission channels in any way.

In all regressions we include both exogenous characteristics such as age and sex and decision variables on workers' resumes such as participation in team sports, choice of university major, hobbies and previous job experience (number of previous jobs and characteristics of last job held). Neal and Johnson (1996) and Heckman (1998) advise against the inclusion of decision variables when estimating labor market discrimination effects because some of the effects of physical attractiveness might be transmitted through these decision variables. However, we can only vary the degree of visual and oral interaction between worker and employer during the wage negotiation process in our experiment but not past decision variables. We therefore follow Hamermesh and Biddle (1994) and only attempt to decompose the marginal effect of looks after accounting for all the other sources of variations in earnings that are usually measured in labor economics.[11]

4 Data Description

4.1 Subject Pool

We conducted 33 experimental sessions at Universidad Nacional de Tucuman, Tucuman, Argentina from August 2002 to March 2003. Participants were recruited at three different university campuses in the city of Tucuman - Universidad Nacional de Tucuman (UNIVERSITY1), Universidad del Norte Santo Tomas de Aquino (UNIVERSITY2), Universidad Tecnologica Nacional (UNIVERSITY3) with approximately 87% of participants coming from the UNIVERSITY1 campus. Special precautions were taken to make sure that participants did not know each other prior to the experiment or could see or communicate with each other upon arrival to the lab. Each participant received a participation fee of 12 Peso plus his earnings from the experiment in cash at the end of the experiment. The average hourly wage at the time in Tucuman was about 6 Peso. For calculating the earnings we used

[11] It is worth noting that we do not find substantial differences between the two specifications.

an exchange rate of 100 points $\cong$ 0.25 Peso. The game lasted from one to one and a half hours and the average earnings were 14.34 Peso in addition to the participation fee. The entire game including instructions and exit questions was played on the computer using a web-based Spanish interface. The instructions were also read aloud and included practice questions with answers to check whether participants had understood the instructions.[12]

Our participants were drawn from a variety of majors (33% from arts and humanities, 46% from sciences, medicine and computers, and 21% from business and economics). Male participants accounted for 58% of our sample. About 50% of our participants have internet access at home which is captured by the indicator variable INTERNET and serves as a proxy for wealth. The resume variables X_j for worker j which every employer could observe consisted of demographic variables (age, sex, matriculation year, university, internet at home and participation in team sports), job experience controls (number of previous jobs and description of last job), university major and hobbies (up to three). Basic summary statistics can be found in table 1.[13]

4.2 Measurement of Beauty

We follow Biddle and Hamermesh (1998) and have frontal facial photographs of all 330 participants evaluated on a scale from 1 to 5 (plain to above average beautiful). Our evaluators were 50 high school students from Tucuman. They were presented with the same facial photographs (in random order) that were previously shown to employers in the three treatments V, VO and FTF. The average inter-rater correlation coefficient of 0.349 is comparable to Biddle and Hamermesh (1998). We construct the variable BEAUTY as the mean over all raters' centered beauty ratings. We obtain rater i's centered beauty rating $\tilde{r}_{ij}$ of subject j by subtracting the rater's average beauty rating $\hat{r}_i$ from each raw rating r_{ij}. This effectively strips out measurement error arising from different perceptions of 'average' beauty.[14] We then normalize the beauty measure by dividing by the standard error. This allows us to interpret regression coefficients on BEAUTY as the effect of a one-standard deviation increase in physical attractiveness. Worker and employer physical at-

[12] The practice questions asked participants to calculate earnings in various scenarios.

[13] The footnote in the table also explains how we coded description of last job held, university major, and hobbies. Additional detailed information is available upon request.

[14] Our results all go through if we use the raw beauty measure: however, the estimated coefficients are slightly smaller and the standard errors slightly bigger as one would expect from using a more noisy measure of physical attractiveness.

tractiveness measures are found in table 2.

4.3 Performance Variables

Our measure of productivity is the the total number of mazes solved during the employment period and workers' estimates after the practice round provide our confidence measure.[15] Table 2 shows the practice and actual performance as well as the confidence of workers. We run our regressions with log ability LNACTUAL and log confidence LNESTIMATED which allows us to interpret estimated coefficients as elasticities. We also use a projected productivity measure LNPROJECTED which extrapolates from the performance time in the practice maze: $LNPROJECTED = ln\left((15 \times 60)/PRACTICE\right)$.[16]

Table 2 also describes the wages (WAGE) and log-wages (LNWAGE) set by employers. Since every employer evaluates 5 workers and there are 165 employers altogether we have 825 data points. SETWAGE is a dummy variable which is set to 1 if the employer's productivity estimate is used to pay the worker and is 0 if the worker receives an average wage.[17]

5 Preliminary Results

We first verify that physical attractiveness does not raise *actual* productivity. However, beauty does raise both the worker's and the employer's productivity *estimates.*

5.1 Determinants of Maze-Solving Productivity

We regress measured log-productivity A_j on all resume variables X_j and physical attractiveness:

$$A_j = \theta X_j + \phi B_j + \epsilon_j \tag{12}$$

[15] Social psychologists use 'self-efficacy' scales to assess optimistic self-beliefs to cope with difficult demands in life (Cassidy and Long, 1996; Lorr and Wunderlich, 1986; Mittag and Schwarzer, 1993). An advantage of our confidence measure is that it is task-specific and has a natural and easily interpretable metric.

[16] Although practice time exceeds the average maze solving time during the employment period the mean value of LNPROJECTED is larger than LNACTUAL. This is a consequence of Jensen's inequality - practice time is a much noisier estimate of ability than total 15 minute productivity.

[17] It is striking how strongly subjects seem to underestimate learning: the average level 1 practice maze takes 127 seconds to solve while the average level 2 maze is solved in only 94 seconds during the employment period. However, both employers and workers' productivity estimates are too low by 20 and 24 percent, respectively.

The results are shown in column (1) of table 3. Note that the coefficient on beauty is *not* significant. We also observe a large gender gap in maze solving productivity in our sample: men solved 10.9 mazes on average during the 15 minute employment period; women only solved 7.8 mazes. Controlling for worker resume does not reduce this gender gap of about 30 percent.[18]

When we also control for practice performance in column (2) of table 3 we see that projected performance is strongly significant but that the magnitude is small: a one percent increase in projected performance increases actual productivity only by 0.16 percent.

5.2 Determinants of Worker Confidence

We next look at the determinants of worker confidence by first regressing confidence on resume variables X_j and beauty B_j shown in column (3) of table 3. In column (4) we add controls for performance in the practice maze P_j and actual ability A_j:

$$C_j = \lambda X_j + \mu P_j + \xi A_j + \pi B_j + \epsilon_j \tag{13}$$

This allows us to test whether workers have private information about their true ability.

Physically attractive workers are substantially more confident: a one standard deviation increase in BEAUTY raises confidence by between 13 and 16 percent. Moreover, workers have private information about their true ability even though they rely more heavily on projected performance: a one percent increase in ability LNACTUAL increases confidence only by .18 percent while a one percent increase in the projected performance LNPROJECTED raises confidence by .43 percent.

Unlike in the ability regression there are no gender effects in the confidence regression. Even though men in our sample are better than women at solving mazes they are not more confident once we control for their true ability. We also add an interaction term between MALE and BEAUTY in column (5) to test for gender specific effects of beauty on confidence. This term is not statistically significant either.

[18]Compared to Gneezy, Niederle, and Rustichini (2003) our gender gap is smaller than their gender gap in the mixed tournament treatment (15 versus 10.8) but larger than the corresponding gap of 1.5 in their piece rate treatment (11.23 versus 9.73).

5.3 Determinants of Employer's Expectations

For each of our five treatments we estimate a simplified version of our empirical model from equation 11:

$$w_{ij} = \alpha X_j + \alpha_P P_j + \beta B_j + \tau S_{ij} + \vartheta S_{ij} * B_j + \psi A_j + \zeta_i + \epsilon_{ij} \tag{14}$$

The coefficient β measures the gross beauty premium and ϑ captures the presence of taste-based discrimination. We use fixed effects estimation in order to control for employer fixed effects ζ_i.

The left side of table 4 shows our estimation results. There is no beauty premium in treatment B in which employers only access resumes without any visual or oral stimuli. In contrast, there are significant beauty premia in all other treatments (V, O, VO and FTF), ranging from 12-13 percent increase in wages for a one standard deviation increase in beauty in treatment V, O, and VO to a 17 percent increase in treatment FTF. These premia are of a similar order of magnitude as the beauty premia found by Hamermesh and Biddle (1994) in their cross-sectional analysis of North American wage data.

The fact that we do not observe a beauty premium in treatment B suggests that we are indeed identifying returns to looks and not just the effect of some correlated omitted variable. It is especially striking that there is a beauty premium in treatment O where workers can only interact orally but not visually with the employer. This provides some preliminary evidence for the oral stereotype effect and the confidence channel. The effects of beauty seem to be particularly strong in the face-to-face interaction - however, this difference is not statistically significant.

The coefficient on LNACTUAL is not statistically significant in all treatments except FTF where it is positive and significant at the 10 percent level. This indicates that our worker characteristics adequately capture the available information to employers. We do not find evidence of direct taste-based discrimination: the coefficient ϑ on SETWAGE*BEAUTY is not significant in any of the five regressions except for treatment V where it has a negative sign. This does not imply that discrimination based on employers' tastes is necessarily unimportant in real world labor markets: if employers derive utility from interacting with an attractive employee over an extended period of time our experimental design cannot account for this effect.

6 Decomposing the Beauty Premium

We next decompose the beauty premium which we found in our wage regressions.

6.1 Decomposition by Treatment

We start by adding controls for worker confidence to our wage regressions from the previous section. We now estimate the full empirical model from equation 11:

$$w_{ij} = \alpha X_j + \alpha_P P_j + \beta B_j + \delta C_j + \tau S_{ij} + \vartheta_V S_{ij} * B_j + \vartheta_O S_{ij} * B_j + \psi A_j + \zeta_i + \epsilon_{ij} \quad (15)$$

Results are on the right hand side of table 4.

The residual beauty premium is measured by the coefficient on BEAUTY and the confidence channel by the coefficient on LNESTIMATED. First of all, we note that there is a significant return to confidence in treatments O, VO and FTF where workers can interact orally with employers. We do not find statistically significant confidence premia in treatments B and V which we would expect since there is no oral communication between worker and employer in these treatments. However, we cannot reject equality of the confidence premia across treatments. A one percent increase in confidence increases wages by about 0.2 percent in treatments O and VO and .3 percent in treatment FTF. Notably, the confidence premium in treatment VO is not significantly larger than in treatment O (if anything it is smaller). This suggests that the employer is unaware that beauty boosts confidence - otherwise she would be able to correct for beauty in the VO treatment and apply a larger weight on confidence.

Hamermesh and Biddle (1994) include measures of self-esteem in their wage cross-sectional regressions and find that these measures are significant just as the confidence variable is in our analysis. However, there is little effect on the size of the beauty premium in their estimation and unlike us they observe only a weak correlation between beauty and self-esteem. This might be the result of greater measurement error of confidence. Hamermesh and Biddle (1994) have to rely on a psychometric measure of general self-esteem in their survey data whereas we can extract a cardinal measure of confidence in solving the specific experimental task with a natural scale. Furthermore, our experimental setup allows us to interpret the coefficient on confidence as a causal effect rather than a correlation coefficient: we do not have to worry about reverse causality such that more highly paid subjects enjoy greater self-esteem. Finally, the fact that confidence only matters in the treatments with oral interaction indicates that our confidence measure is not just a proxy for omitted variables.

The beauty premia in treatments O, VO and FTF decline when we control for confidence but are still significantly different from 0. This decline suggests that at least part of the beauty premium is transmitted through greater confidence of physically-attractive workers. We can decompose it in treatments O, VO and FTF by using the following back of the envelope calculation. One standard deviation in beauty increases confidence by about 13 percent according to our regression results in table 3 (we assume SETWAGE is zero for simplicity). In treatment O a one percent increase in confidence increases wages by 0.20 percent. Therefore, the total increase in wages of a one standard deviation increase in beauty which is transmitted through the confidence channel is 13×0.20 percent $= 2.6$ percent. The residual beauty premium after controlling for confidence in treatment O is 8.7 percent for a one standard deviation increase in beauty. The sum of both effects is 11.3 percent which is reasonably close to the gross beauty premium of 12.8 percent that we estimated for treatment O. For completeness, table 5 presents the same decomposition for treatments VO and FTF.

We attribute the estimated residual beauty premia to the visual and oral stereotype channels that make the beautiful appear more able in the eyes of the employer. The visual stereotype effect (treatment V) raises wages by about 10.5 percent for each one standard deviation increase in beauty when employers only see a picture of the worker. Interestingly, there still remains a strong residual beauty premium in treatment O where employers have no visual information about the worker but only interact verbally over the phone. This suggests that beauty is correlated with certain oral communication skills other than confidence that raise employers' estimates. The visual and oral stereotype effects do not seem additive: in treatments VO and FTF where employers and workers interact both visually and orally the beauty premia are only marginally greater but not significantly so.

6.2 Decomposition across Treatments

We finally estimate the full empirical model across all five treatments

$$\begin{aligned} w_{ij} &= \alpha X_j + \alpha_P P_j + \sum_t \alpha_{P,t} T_t * P_j + \beta_0 B_j + \delta_0 C_j + \sum_t \beta_t T_t * B_j + \sum_t \delta_t T_t * C_j + \\ &+ \tau S_{ij} + \vartheta_V T_V * S_{ij} * B_j + \vartheta_O T_O * S_{ij} * C_j + \psi A_j + \zeta_i + \epsilon_{ij} \qquad (16) \end{aligned}$$

where $t = V, O, VO, FTF$. The specification is the same as in equation 11 except that we add the indicator variables T_{VO} for combined visual and oral interactions (treatments VO and FTF) and T_{FTF} for face-to-face communication. By interacting these two additional variables with beauty and confidence we can check whether the visual and oral stereotype channels are additive and whether there is an additional effect from face-to-face communication. Moreover, we allow the coefficients on the practice performance to vary across the five treatments. The regression results are in table 6.[19]

The coefficients on BEAUTY*VISUAL and BEAUTY*AUDIO capture the visual and oral stereotype channels: a one standard deviation increase in beauty provides a 9.4 percent and 10.3 percent wage gain respectively. The confidence channel raises the wage by about 0.27 percent for each one percent increase in confidence. This translates into a 3.6 percent increase in wages for a one standard deviation increase in beauty. Since the average number of mazes estimated by participants is 7, a subject who believes he could do one more maze than average would register a 14% increase in confidence, which in turn translates into a 4% increase in wage. Face-to-face interaction does not amplify the stereotype and confidence channels significantly.

To summarize, we find that about 15-20 percent of the beauty premium is transmitted through the confidence channel and about 40 percent each through the visual and oral interaction channels. However, this decomposition comes with the caveat that the visual and oral stereotype channels are not fully additive: the coefficient on BEAUTY*VISUAL*AUDIO is negative and weakly significant.

7 Conclusion

We decompose the beauty premium in an experimental labor market and identify three transmission channels: the visual and oral stereotype channel and the confidence channel. Our results are complementary to the existing labor literature starting with Hamermesh and Biddle (1994) who identified the beauty premium in real data.

As with a vast body of experimental studies, standard criticisms of our student subject pool apply. The experience of real-world human resource officers might make them less susceptible to physical features of the applicants. Another important caveat is that we only model the interview process. If employer and

[19] This additive decomposition is appropriate only for the case when the employer is unaware of the confidence-boosting effects of beauty. If she could filter out this effect under visual interaction we would have expected to estimate a larger coefficient δ on worker confidence in treatment VO versus treatment O in the previous section which was not the case.

worker interact repeatedly over the long-term direct taste-based discrimination might again become a more important contributor to the beauty premium and stereotype and confidence effects might become less relevant. However, we find it encouraging that our experiment generates a sizable beauty premium of the right order of magnitude which gives us some confidence that our decomposition applies more generally.

If one is willing to extrapolate from our experiment to the labor market more generally we can draw two main policy implications. First, 'blind' interview procedures such as telephone interviews can reduce the beauty premium.[20] Second and perhaps more surprisingly, our results suggest that the beauty premium would decline even more strongly by preventing oral interaction between employer and employee. However, such a policy would likely decrease the quality of job matches along other dimensions because employers learn valuable private information during the interview stage.

While we focus on decomposition of the beauty premium in this paper, our methodology can be fruitfully adopted to study the causes of discriminatory pay differentials in other settings.

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[20]Similarly, Goldin and Rouse (2000) find that 'blind' auditions increase the probability of female musicians being hired or promoted.

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Table 1: Summary statistics - characteristics of workers and employers

Variable	Mean	Std. Dev.
Workers - Demographic Variables		
AGE	22.963	3.212
MALE	0.564	0.497
MATRIC	1998.317	2.784
UNIVERSITY1	0.848	0.36
UNIVERSITY2	0.091	0.288
UNIVERSITY3	0.061	0.239
INTERNET	0.515	0.501
TEAMSPORT	0.612	0.489
Workers - Job Experience		
INTERVIEWS	1.267	1.303
PREVJOBS	1.188	1.337
JOB_EDUCATION	0.067	0.25
JOB_COMPUTERS	0.024	0.154
JOB_RETAIL	0.091	0.288
JOB_BUSINESS	0.067	0.25
JOB_GOVERNMENT	0.036	0.188
JOB_ARTS	0.036	0.188
JOB_FOOD	0.006	0.078
JOB_INDUSTRY	0.006	0.078
INTERACTION_DEGREE	0.636	1.357
Workers - College Major		
MAJOR_BUSINESS	0.207	0.407
MAJOR_SCIENCE	0.134	0.342
MAJOR_COMPUTERS	0.22	0.415
MAJOR_HUMANITIES	0.244	0.431
MAJOR_MEDICINE	0.104	0.306
MAJOR_ARTS	0.091	0.289
Workers - Hobbies		
HOBBY_COMPUTERS	0.273	0.46
HOBBY_RECREATION	0.855	0.791
HOBBY_ARTS	0.830	0.746
HOBBY_SPORT	0.655	0.738
Employers - Demographic Variables		
EMP_AGE	22.673	2.482
EMP_MALE	0.604	0.491
EMP_MATRIC	1998.659	2.364
EMP_UNIVERSITY1	0.902	0.298
EMP_UNIVERSITY2	0.061	0.24
EMP_UNIVERSITY3	0.037	0.188
EMP_INTERNET	0.482	0.501
EMP_TEAMSPORT	0.604	0.491

$N = 165$

Employer variables start with the prefix EMP. MATRIC is the undergraduate matriculation year. UNIVERSITY1, UNIVERSITY2, and UNIVERSITY3 are indicator variables for the three universities at which subjects are studying. INTERNET is an indicator variable for having an internet connection at home and TEAMSPORT captures whether a subject participates in team sports. Intended or actual majors are summarized by variables MAJOR_BUSINESS, MAJOR_SCIENCE, MAJOR_COMPUTERS, MAJOR_HUMANITIES, MAJOR_MEDICINE, MAJOR_ARTS indicating whether a subject concentrates on business, science, information technology, humanities, medicine, or arts. The number of previous jobs held by a subject are captured by PREVJOBS and the number of job interviews by INTERVIEWS. The nature of previous employment for those with work experience is denoted by variables JOB_EDUCATION, JOB_COMPUTERS, JOB_RETAIL, JOB_BUSINESS, JOB_GOVERNMENT, JOB_ARTS, JOB_FOOD, JOB_INDUSTRY indicating employment in education, information technology, retail sales, business, public sector, arts, food production and service, and industry. INTERACTION_DEGREE is a variable that describes the intensity of interpersonal interactions required in each job on a scale from 0 to 5, 0 implying no interactions and 5 being the most intense as for a secretary or a waiter. Hobbies were coded using HOBBY_COMPUTERS for computers, HOBBY_RECREATION for recreation (e.g. watching TV or listening to music), HOBBY_ARTS for creative tasks (e.g., writing, drawing, or composing music), HOBBY_SPORT for sports. If a subject reported several hobbies that were of the same category, the number of hobbies were added up and a total score reported. No hobbies in a certain category resulted in an entry of 0.

Table 2: Summary statistics - physical attractiveness, maze solving performance and wages

Variable	Mean	Std. Dev.	Variable	Mean	Std. Dev.
Physical Attractiveness			*Confidence*		
BEAUTY	0.024	1	ESTIMATED	7.255	4.013
EMP_BEAUTY	0.026	1	LNESTIMATED	1.829	0.573
Maze Performance			*Wages*		
PRACTICE	126.691	92.292	WAGE	7.727	5.13
ACTUAL	9.527	3.874	LNWAGE	1.863	0.612
LNPROJECTED	2.225	0.764	SETWAGE	0.531	0.499
LNACTUAL	2.149	0.504			

$N = 165$ for all variables except WAGE, SETWAGE, LNWAGE ($N = 825$)

BEAUTY and EMP_BEAUTY denote the physical attractiveness of worker/employer respectively. Both measures are detrended and the standard deviation is normalized to 1. The raw performance measures are PRACTICE for the time (measured in seconds) to solve the practice maze and ACTUAL for the number of mazes solved during the 15 minute employment period. LNPROJECTED is the log of the predicted number of mazes solved during the employment period based on the practice performance. LNACTUAL is the log of actual performance. The confidence measures are ESTIMATED (estimated performance) and LNESTIMATED, the log of estimated performance. WAGE denotes the employer estimate of the performance of a worker and LNWAGE is the log of this estimate. SETWAGE is set to 1 if the employer estimate is contributing to the compensation of the worker.

Table 3: The impact of practice performance and beauty on maze solving ability and confidence

	LNACTUAL		LNESTIMATED		
Variable	(1)	(2)	(3)	(4)	(5)
AGE	0.081	0.038	0.181*	0.018	0.018
	(0.065)	(0.064)	(0.074)	(0.060)	(0.060)
AGE*AGE	-0.002†	-0.001	-0.003*	0.000	0.000
	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)
MALE	0.331**	0.303**	0.221*	0.015	0.015
	(0.086)	(0.081)	(0.097)	(0.080)	(0.081)
UNIVERSITY2	-0.113	-0.088	-0.026	0.035	0.036
	(0.143)	(0.139)	(0.163)	(0.127)	(0.128)
UNIVERSITY3	0.042	0.115	-0.358	-0.183	-0.184
	(0.201)	(0.197)	(0.229)	(0.179)	(0.180)
INTERNET	0.158†	0.136†	0.089	0.042	0.042
	(0.083)	(0.080)	(0.094)	(0.074)	(0.075)
TEAMSPORT	0.062	0.054	0.133	0.127	0.128
	(0.088)	(0.085)	(0.101)	(0.078)	(0.079)
PREVJOBS	0.057	0.052	0.012	-0.003	-0.003
	(0.037)	(0.036)	(0.042)	(0.033)	(0.033)
LNACTUAL				0.177*	0.177*
				(0.078)	(0.079)
LNPROJECTED		0.160**		0.429**	0.429**
		(0.054)		(0.051)	(0.051)
BEAUTY	-0.034		0.162**	0.135**	0.133**
	(0.042)		(0.048)	(0.038)	(0.051)
BEAUTY*MALE					0.002
					(0.075)
N	163	163	163	163	163
R^2	0.323	0.362	0.304	0.587	0.587

Significance levels: $\dagger$: 10% $*$: 5% $**$: 1%

The dependent variable is LNACTUAL in columns (1) and (2) and LNESTIMATED in columns (3), (4) and (5); standard errors are shown in paranthesis. The base university is UNIVERSITY1. All regressions include the following additional resume controls: choice of college major, hobby variables and previous job market experience.

Table 4: Gross and decomposed beauty premia in treatments (B) to (FTF)

Variable	Gross beauty premia					Decomposed beauty premia with worker confidence				
	(B)	(V)	(O)	(VO)	(FTF)	(B)	(V)	(O)	(VO)	(FTF)
AGE	0.009	0.007	-0.014	0.088*	-0.121*	0.011	-0.002	-0.023	0.081*	-0.138**
	(0.047)	(0.042)	(0.038)	(0.040)	(0.048)	(0.048)	(0.043)	(0.036)	(0.039)	(0.046)
AGE*AGE	0.000	0.000	0.000	-0.002*	0.002*	0.000	0.000	0.000	-0.001*	0.002*
	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)
MALE	0.050	0.069	0.130*	0.180**	0.083	0.052	0.054	0.120*	0.173**	0.085
	(0.071)	(0.064)	(0.057)	(0.059)	(0.071)	(0.071)	(0.066)	(0.053)	(0.057)	(0.068)
LNPROJECTED	0.403**	0.397**	0.407**	0.375**	0.372**	0.414**	0.386**	0.322**	0.302**	0.298**
	(0.043)	(0.038)	(0.035)	(0.036)	(0.043)	(0.053)	(0.046)	(0.039)	(0.044)	(0.050)
LNACTUAL	-0.038	0.010	-0.014	0.095†	-0.017	-0.033	0.014	-0.049	0.064	-0.046
	(0.063)	(0.057)	(0.051)	(0.056)	(0.064)	(0.065)	(0.059)	(0.050)	(0.055)	(0.062)
BEAUTY	0.017	0.131**	0.129**	0.124**	0.167**	0.018	0.114*	0.087*	0.098**	0.121**
	(0.040)	(0.042)	(0.034)	(0.036)	(0.043)	(0.042)	(0.045)	(0.034)	(0.037)	(0.043)
SETWAGE	-0.010	-0.072	0.098*	-0.046	0.033	0.052	0.106	0.059	-0.023	0.555**
	(0.055)	(0.052)	(0.046)	(0.048)	(0.057)	(0.207)	(0.206)	(0.151)	(0.176)	(0.207)
SETWAGE*BEAUTY	-0.058	-0.099†	0.005	0.022	-0.044	-0.053	-0.088	0.022	0.013	0.002
	(0.057)	(0.053)	(0.048)	(0.050)	(0.058)	(0.058)	(0.055)	(0.046)	(0.051)	(0.058)
LNESTIMATED						-0.004	0.100	0.205**	0.186**	0.328**
						(0.098)	(0.094)	(0.064)	(0.068)	(0.097)
SETWAGE*LNESTIMATED						-0.034	-0.094	0.025	-0.009	-0.282**
						(0.110)	(0.108)	(0.078)	(0.091)	(0.107)
N	163	161	163	162	163	163	161	163	162	163
R^2	0.61	0.696	0.751	0.776	0.605	0.611	0.700	0.783	0.796	0.647

Significance levels: † : 10% $*$: 5% $**$: 1%

The dependent variable is LNWAGE; standard errors are shown in paranthesis. All regressions include the following additional resume controls: university dummies, participation in team sports, choice of college major, hobby variables and previous job market experience. All regressions are fixed-effects regressions with employer fixed effects.

Table 5: Contribution of confidence channel to gross beauty premium in treatments O, VO and FTF

Treatment	Beauty Premium (controlled for confidence)	Confidence Channel	Gross Beauty Premium
O	8.7	2.6	12.8
VO	9.8	2.4	12.3
FTF	12.1	4.3	16.7

The entries are wage increases in percentage points for each one standard deviation increase in beauty. They are calculated using the estimated coefficients in tables 3 and 4. SETWAGE is assumed to be zero.

Table 6: Estimation of full empirical model

Variable	(1)
LNPROJECTED	0.409^{**}
	(0.043)
LNPROJECTED*VISUAL	0.007
	(0.059)
LNPROJECTED*AUDIO	-0.129^{*}
	(0.059)
LNPROJECTED*VISUAL*AUDIO	0.056
	(0.084)
LNPROJECTED*FTF	-0.069
	(0.060)
LNACTUAL	-0.004
	(0.027)
BEAUTY	-0.010
	(0.031)
BEAUTY*VISUAL	0.094^{*}
	(0.043)
BEAUTY*AUDIO	0.103^{**}
	(0.035)
BEAUTY*VISUAL*AUDIO	$-0.097^{\dagger}$
	(0.050)
BEAUTY*FTF	0.052
	(0.035)
LNESTIMATED	0.018
	(0.065)
LNESTIMATED*VISUAL	0.034
	(0.083)
LNESTIMATED*AUDIO	0.265^{**}
	(0.083)
LNESTIMATED*VISUAL*AUDIO	-0.056
	(0.117)
LNESTIMATED*FTF	-0.116
	(0.083)
N	812
R^2	0.627

Significance levels: $\dagger$: 10% $*$: 5% $**$: 1%

The dependent variable is LNWAGE; standard errors are shown in parenthesis. The base university is UNIVERSITY1. The regression includes the following resume controls: demographic variables (sex, age and age squared, internet at home, participation in team sports, choice of college major, hobby variables and previous job market experience. The regression also includes SETWAGE, and SETWAGE interacted with BEAUTY and LNESTIMATED.