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Beauty and the beast in the labor market: Evidence from a distribution regression approach*

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Abstract

We apply an innovative technique to allow for differential effects of physical appearance across the wage distribution, as traditional methods confound opposing effects. Counterfactual wage distributions constructed using distribution regression, show that unattractive women are more likely to earn less than the median wage, particularly in professions where physical appearance is important. We also find a premium for well-paid attractive men in these professions. A comparison with results from traditional models shows that the characteristics of people in different physical appearance classes contributes to the effects identified using the latter and only a small portion could be discrimination.

Keywords: Wages; Distribution; Physical Appearance; Discrimination
JEL classification codes: D31; J24; J30; J70

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'All that glitters is not gold' -W. Shakespeare

1 Introduction

Like in so many areas of life, Shakespeare had excellent insight into the sometimes misleading effects of physical appearance. In this paper, we examine whether the glitter of an appealing physical appearance leads to higher pay. It has been shown that beauty is positively related to earnings in the labor market. Hamermesh and Biddle (1994), in their seminal paper, show the existence of an average wage penalty of 5-10% for being plain and an average wage premium of 5-10% for being beautiful in the US and Canada. Most other studies that find a positive effect of looks on earnings also identify average effects (Biddle and Hamermesh (1998), Harper (2000), Hamermesh et al. (2002), Mobius and Rosenblat (2006) and Sen et al. (2010)). While measuring average effects is quite informative and convenient, it also has substantial drawbacks, as opposing effects that exist across the distribution may be confounded in the summary effect. This has already been discovered for other variables that affect wages, such as gender, for example (Bonjour and Gerfin (2001)). As far as we know, the varying effect of beauty on wages throughout the distribution has not been examined. The effect may vary across the distribution because different points of the distribution correspond to different job types, which pay a different premium for looks. Better looking people, *ceteris paribus*, may have more opportunities to advance and have higher wages, while less good looking people may need to compensate with their qualifications and other traits, and the extent of these differences may vary depending on where the individual is located in the distribution. In this paper, our goal is to examine the effect of beauty on earnings across the wage distribution using an innovative technique and new data.

Our contribution to the literature is three-fold. First, we demonstrate that the effect of beauty varies across the wage distribution. Next, we demonstrate how distribution regression, a method seldom used in this literature and initially used to model excess returns on financial markets, could prove a useful tool in decomposing wage differentials by physical appearance across the wage distribution. Finally, given that data on physical appearance is fairly scarce, having access to a unique dataset, we provide new results on the effect of beauty on wages in a new country.

Our strategy is as follows. We start by estimating a Heckman selection model for wages at the mean. Next, suspecting that there is some variation in the effect of physical appearance in different areas of the wage distribution, we estimate a series of quantile regressions

(QR) to serve as a benchmark. Finally, discovering that there is indeed variation across the distribution, we progress to distribution regression (DR) to model counterfactual distributions of wages for groups of people classed by physical appearance. Modeling wage distributions using DR is related to QR in that DR models the conditional probability of being located in particular quantile group while QR models the conditional wage of a particular quantile group. We model entire counterfactual distributions of wages, in order to pinpoint wage gaps between different groups of people at every point of the distribution. An Oaxaca-Blinder style decomposition of these counterfactual distributions allows us to identify the existence or absence of beauty premia and plain penalties. We show that there are indeed differences in the effect of beauty across the earnings distribution. The effect varies for men and women and by occupations. We apply these three methodologies to a unique dataset from Luxembourg.

In Section 2 we provide some background information on prior modeling of the effect of physical appearance on various outcome variables and the previous literature. In Section 3 we outline our methodology. Section 4 describes the data and variable construction. Section 5 discusses the results and Section 7 concludes.

2 Background

Biddle and Hamermesh (1998), Harper (2000), Hamermesh et al. (2002), Mobius and Rosenblat (2006) and Sen et al. (2010), using different methods, all find evidence of a positive relationship between physical appearance and earnings. This relationship has been shown to be different for men and women. A theoretical framework on this issue is offered by Jackson (1992). In her model, both the sociobiological (reproductive potential) and sociocultural (cultural values) perspectives predict that physical attractiveness has greater implications for females than males. A number of other studies have validated this. Frieze et al. (1991), for example consider the relationship between facial attractiveness and income. They discover that attractive males are able to secure higher starting salaries and that the earnings differentials are persistent over time. The most attractive female graduates do not earn higher starting salaries but they do earn more income later in their careers.

There are a number of possible explanations for the relationship between physical appearance and earnings. These have been categorized into direct and indirect effects. Direct effects, first elaborated by Hamermesh and Biddle (1994), include pure employer discrimination, customer discrimination and occupational crowding. The indirect effects are harder to pin down but a number of theories have been put forward. Mocan and Tekin (2010) find evidence that being an unattractive student in high school may hinder human capital development due to preferential treatment. This will have a knock-on effect on earnings later in life. There are also effects through the marriage market. Barro (1998) finds that less attractive women are much less likely to marry than attractive women and tend to have husbands with sharply lower earnings. While this does not directly affect the woman's earnings, it does affect total household earnings.

3 Methodology

As a first step of our empirical strategy, we will test the hypotheses put forth by Hamermesh and Biddle (1994), at the mean, controlling for selection into employment, and using different quantile groups. We then apply the DR approach pioneered by Foresi and Peracchi (1995) to examine the effect of beauty across the whole earnings distribution. We construct flexible counterfactual wage distributions, using the group of men and women with self-assessed average physical appearance as the baseline, to see whether differences across beauty groups are driven by differences in characteristics or differences in the wage function (coefficients).

3.1 Hamermesh and Biddle selection model

Hamermesh and Biddle (1994) put forward three possible reasons for earnings differentials based on physical appearance: customer discrimination, employer discrimination, and occupational sorting. The first of these assumes that looks may enhance productivity at work. In this case, physical appearance may enhance the worker's ability to engage in productive interactions with coworkers or customers in certain occupations because they prefer interacting with better looking individuals. In this framework there will be a premium for good looks and workers will sort into the occupation paying the highest wage. Attractive and unattractive workers may be in the same occupation if the unattractive worker also has other productivity enhancing characteristics that affect the wage.

The occupational sorting hypothesis suggests that occupational requirements for beauty create independent effects on wages and, as a result, lead people to select certain occupations based on their looks and the expected returns to those looks. In this situation unattractive workers may be confined to certain occupations which, consequently, depresses the wages of all workers in those occupations.

Finally, there may be employer discrimination. Employers may have a distaste for unattractive employees and this produces a differential in earnings, but no systematic sorting into occupations. In this case, we do not expect any systematic differences in the beauty premium across occupations.

To test these effects formally our wage function is expressed in the following way:

$$w_i = \beta_0 + \beta_1 X_i + \beta_2 \theta_i + \beta_3 D_i + \beta_4 \theta_i D_i + \epsilon_i$$

θ_i is a vector indicating whether someone is physically attractive or not; D_i is an indicator variable for whether person i is in an occupation where looks could enhance productivity and zero otherwise; X_i is a vector of other individual level characteristics; and ϵ_i are the residuals. The occupational crowding hypothesis would suggest that $\beta_3 > 0$ and unattractive workers would have lower wages. The productivity hypothesis would imply that worker's looks matter in occupations where beauty is important and there is a possibility of sorting according to looks ($\beta_4 > 0$ and $\beta_2 = \beta_3 = 0$). The situation where we find a robust effect of individual looks on earnings, independent of occupations ($\beta_2 > 0$ and $\beta_3 = \beta_4 = 0$) could be the result of employer discrimination.

As a first step, we estimate the Heckman (1979) two-step model to correct for selection into work separately for men and women. Let's assume $P(E = 1|Z) = \Phi(Z\gamma)$ is the probability that an individual will be employed ($E = 1$ if employed and 0 otherwise). Z is a vector of characteristics that affect the probability of being employed and Φ is the cumulative normal distribution function. Then $w*$ is the potential wage and is not observed if $E = 0$

$$w* = X\beta + u \tag{1}$$

where X is a vector of characteristics influencing wages (such as company size, contract type, nationality, education, experience, public sector). Then the expected wage, assuming that the error term in the selection equation, ε and u, are jointly normal is

$$E[w|X, E = 1] = X\beta + E[u|X, E = 1] = X\beta + \rho\sigma_u\lambda(Z\gamma) \tag{2}$$

where ρ is the correlation coefficient between ε and u; σ_u is the standard deviation of u and $\lambda(Z\gamma)$ is the Inverse Mills' Ratio $[\frac{\phi(.)}{\Phi(.)}]$ evaluated at $Z\gamma$. The equation tested is as follows:

$$w_i = \beta_0 + \beta_1 X_i + \underbrace{\beta_2}_{\substack{\text{employer}\\ \text{discrimination}}} \theta_i + \underbrace{\beta_3}_{\substack{\text{occupational}\\ \text{sorting}}} D_i + \underbrace{\beta_4}_{\substack{\text{customer}\\ \text{discrimination}}} \theta_i D_i + \underbrace{\rho\sigma_u\lambda(Z\gamma)}_{\substack{\text{selection}\\ \text{correction}}} + \epsilon_i \quad (3)$$

where θ_i is a vector of physical appearance dummies (above average looking, below average looking) and D_i is an indicator variable for an occupation where looks could enhance productivity (direction, supervisors, salespeople, service providers) and zero otherwise (academics, administrators, manual laborers).

3.2 Quantile regressions

Recent research into discrimination and wage gaps has increasingly focused on more global methods than the evaluation of differences at the mean. Quantile regression (QR), first introduced by Koenker and Bassett (1978) is a widely used tool which allows characteristics to have different returns at different quantiles of the residual distribution. Buchinsky (1998) proposed a method to correct for selection bias in quantile regressions. However, this methodology has recently been called into question by Huber and Melly (2011) due to the underlying assumption that the errors are independent of the regressors, implying that all quantile and mean functions should be parallel. For this reason, and because we find no evidence of a selection bias engendered by selection into employment in the first step our our econometric analysis, we do not conduct any selection correction in the QR framework. The quantile regression model corresponding to Eq 3 will be the following:

$$w_i = \beta_0^{(p)} + \beta_1^{(p)} X_i + \underbrace{\beta_2^{(p)}}_{\substack{\text{employer}\\ \text{discrimination}}} \theta_i + \underbrace{\beta_3^{(p)}}_{\substack{\text{occupational}\\ \text{sorting}}} D_i + \underbrace{\beta_4^{(p)}}_{\substack{\text{customer}\\ \text{discrimination}}} \theta_i D_i + \epsilon_i^{(p)} \quad (4)$$

where $p \in (0, 1)$ indicates the proportion of the population having wages below the quantile at p and the pth quantile of the error term $\epsilon^{(p)}$ is assumed to be zero. We will look at 5 conditional quantiles $p = 0.1, 0.25, 0.5, 0.75, 0.9$

3.3 Distribution regression

As we will show in section 5, there are indeed differences in the effect of beauty on wages across the distribution. Therefore, in the final econometric stage, we extend our analysis to the entire distribution of wages, so that we can pinpoint the exact portion of the wage distribution affected by differing returns to physical appearance. We use distribution regression (DR), a methodology pioneered by Foresi and Peracchi (1995) to model excess returns on financial markets, which is seldom exploited in this literature. DR can be thought of as the flip-side of QR. While DR models the location of conditional wages in the wage distribution (between 0 and 1), QR models the conditional wage at a particular location (e.g. the first quantile group, $p = 0.1$) in the distribution. We choose to use DR to present our main results as it is, arguably, simpler and more intuitive to implement. Also, in the event that an omitted variable such as self-confidence is driving both the wage and the self-assessed physical appearance of an individual, the fact that DR compares people at specific wage levels, rather than at the mean or at particular quantile groups, at least partially negates this problem. DR also provides a convenient graphical way to display results. Another advantage of DR, which we do not exploit in this paper, is the fact that, in contrast to QR, it can be simply extended to allow for selection correction.

In a technical paper, Chernozhukov et al. (2009) applied this methodology to examine the effect of labor market institutions on wage inquality in the U.S. In this paper, we are interested in the difference in the conditional distribution of wages for men and women of different classes of physical appearance, given explanatory variables, while holding the marginal distribution of these covariates constant. In practical terms, this involves running a series of probit models at each point in the wage distribution separately for men and women for each class of physical appearance. The dependent variable is binary and takes the value of 1 if the individual has an hourly wage below w, where w takes the value of each point of the wage distribution sequentially, and 0 otherwise. These models are used to predict the probability that an individual has an hourly wage below w in the distribution, as well as predicting what this probability would be if the individual was compensated as if they belonged to a different physical appearance group. We employ an Oaxaca-Blinder style decomposition (Oaxaca (1973)Blinder (1973)) to the marginal distributions of each physical appearance group to identify what the distribution of wages would be for men and women separately, in the absence of premia and penalties based on physical appearance. We can thus identify what portion of the wage gap between groups is due to different characteristics, and what part is unexplained, and may therefore be due to discrimination.

Starting from estimates of the conditional distribution of the wages of females (f) with average (av) self-assessed beauty, given human capital and job characteristics, we recover estimates of the marginal distribution by integration of the conditional distributions over job and human capital characteristics:

$$F_{f,av}^{f,av}(w) = \int_{\Omega_x} F^{f,av}(w|x)\, h_{f,av}(x)\, dx \tag{5}$$

where $F^{f,av}(\cdot|x)$ is the conditional cumulative wage distribution function for human capital characteristics x and $h_{f,av}$ is the density distribution of human capital and job characteristics. Both functions are for female workers with average self-assessed beauty as indicated by subscripts f, av.

The marginal distribution for female workers with above (ab) and below (b) average self-assessed beauty and the corresponding distributions for male workers can be recovered analogously.

Sample estimates are obtained by replacing $F^{f,av}(\cdot|x)$ by estimates $\hat{F}^{f,av}(\cdot|x)$ in equation (5), and by averaging over our sample of N female workers with average physical appearance:

$$\hat{F}_{f,av}^{f,av}(w) = \sum_{i=1}^{N_{f,av}} \hat{F}^{f,av}(w|x_i) \tag{6}$$

We now have a straightforward way to create counterfactual marginal wage distributions. For example,

$$\hat{F}_{f,ab}^{f,av}(w) = \sum_{i=1}^{N_{f,ab}} \hat{F}^{f,av}(w|x_i) \tag{7}$$

is a counterfactual distribution that represents the distribution that would be observed among female workers with above average physical characteristics, if the conditional wage distribution among female workers with an average physical appearance prevailed. We illustrate this graphically in Figure 1. Denote:

$$AVav\_f = \hat{F}_{f,av}^{f,av}(w)$$
$$ABab\_f = \hat{F}_{f,ab}^{f,ab}(w)$$
$$AVab\_f = \hat{F}_{f,ab}^{f,av}(w)$$

$AVav\_f$ shows the predicted wage distribution for average looking women while $ABab\_f$ shows the predicted wage distribution of above average looking women. $AVab\_f$ then shows the wage distribution of above average looking women that would have prevailed if they were paid as average looking women. Decomposing the wage gap, we therefore find two components. The difference between the $AVab\_f$ and $AVav\_f$ curves shows the wage gap that is due to human capital and job characteristics (the well-known "characteristics gap"). In this case, it is clear that average women have "better" characteristics than their above average counterparts in terms of wage determination, although the size of these differences varies across the distribution. At the top of the distribution it is smaller than at the bottom. This can also be seen in the top right panel in Figure 2.[1] The difference between the $ABab\_f$ and $AVab\_f$ curves depicts the "coefficient" effect, or the unexplained effect. In the literature this is often interpreted as discrimination although, here, we refer to it as the beauty premium or penalty. In this case, we find that above average women would be paid more if they were rewarded as average women for the same characteristics (beauty penalty). Therefore, the wage premium is in favor of average looking women, compared to above average looking women. This can also be seen in the top left panel in Figure 2.[2]

More formally, the gap between average looking workers and their over and under average looking counterparts can be decomposed into a part attributable to characteristics and a part due to coefficients. For example, to decompose the difference in the wage distribution of above average and average looking women, we employ the following expression:

$$F_{f,ab}^{f,ab}(w) - F_{f,av}^{f,av}(w) = [\hat{F}_{f,ab}^{f,ab}(w) - \hat{F}_{f,ab}^{f,av}(w)] + [\hat{F}_{f,ab}^{f,av}(w) - \hat{F}_{f,av}^{f,av}(w)] \tag{8}$$

The first expression identifies the coefficient effect for the wage distribution. This represents the difference in the marginal distribution of wages for above average and average looking women, that cannot be explained by human capital or job characteristics. A positive value would indicate that there is a penalty to being above average looking at w, compared to being average looking. The second expression identifies the characteristic effect, which gives the difference in the marginal distribution that is due to the fact that above average and average looking women have different human capital and job characteristics. A positive value would indicate that average looking people have better human capital and labor market characteristics than above average looking people. We perform this decomposition analogously for below average and average looking women and we also perform both of these decompositions for men.

[1] The gap can also be interpreted in terms of probabilities. In this case a positive gap indicates that due to their human capital and job characteristics, above average women have a higher probability of having lower wages than average women. In other words, if above average women were paid as average women they will would still be paid less than average women.

[2] In terms of probabilities, a positive gap indicates that if above average women were paid as average women, they would have a higher probability of getting higher pay.

4 Data and Descriptives

In our analysis, we use the new discrimination module of the 2007 wave of PSELL3/EU-SILC for Luxembourg. Our main variables of interest are the respondent's opinion of how important physical appearance is in the labor market, their self-assessed physical appearance and their hourly wages. The physical appearance variables are self-perceived and are assumed to be in no way influenced by interviewers or other factors related to data collection.

4.1 Beauty Categories

We take advantage of two questions in the special discrimination module regarding physical appearance. The first refers to the role of beauty in the work place: Do you think that the physical appearance (height, corpulence, color of the skin, face, etc.) plays an important role in the professional life and the career? The answer is on a 1-5 scale (very important, important, of little importance, not important, no opinion). We use this question to construct two types of occupations described in the next section.

The second question refers to self-assessed of beauty: Considering now your general physical appearance (height, corpulence, color of the skin, face, etc.). On a scale of 1 to 10, 1 being 'very little attractive' and 10 being 'very attractive' how do you think people around you rate your physical appearance (in comparison to others of the same age and sex)?

Although the question asks for a self-assessment of beauty, the comparative nature of the question introduces an objective element, which is less likely to confound the physical appearance and self-confidence of the respondent. We use this second question to create 3 categories of beauty: above average, average and below average. We examine the response behavior for this variable by age and gender and find the mean and median to be between 6 and 7, corresponding to the responses of just under 40% of the sample. 27% report physical appearance above 7 and and 33% report physical appearance under 6. Consequently we define an individual with above average looks if the variable equals 8-10, average if it equal 6 or 7 and below average if equals 1-5. In table 1 Panel A we see that working women and men are equally likely to report above average, average and below averge looks.

4.2 Occupation: Dressy and Non-dressy

In order to test our hypotheses we need to identify the occupations where physical appearance may affect productivity. Figure A1 shows the perceived importance of beauty variable by occupations. The occupations include: executive and legislative professions, supervisors, managers; intellectual professions; intermediate professions; administrative employees; service and sales employees; artists and crafts people; machine operators; and blue collar (including farmers) and non-qualified workers. We classify occupations as *dressy* or *non-dressy*. In the non-dressy category we include occupations where, either most people reported looks as unimportant or the job does not entail a lot of people interaction. This category includes farm workers, artists and crafts people, machine operators and blue-collar workers. In all these occupation people are more likely to state that looks are "not important" than that they are "very important." The dressy occupation includes occupations where human interaction is an important component of day to day activities. These include supervisors and managers, intellectual professions, intermediate professions, administrative employees and service and sales employees. Table 1 Panel B indicates that looks are indeed perceived as being more important in the dressy occupation category than in the non-dressy category and we observe a statistically significant higher concentration of people with good looks in the dressy profession for the whole sample and for women and men separately.

4.3 Sample, Dependent variable and Covariates

Our overall sample consists of 18 to 65 year olds. We exclude those who work more than one job, the self-employed and all those who work over 70 hours per week. We are left with a sample of 2939 women (1578 workers) and 2837 men (2180 workers).

The explanatory variables used to model wages include education, work experience, nationality, marital status, health and job characteristics (dressy profession, temporary, part-time, civil servant, company size). For a description of these variables, see Table A1.

We compare hourly wages across various beauty categories. Table 2 indicates that average looking individuals report the highest wages. This holds for the whole sample and for women and men separately. This difference is not statistically significant only when we compare average looking women to those with under average looks.

Looking at the two occupation categories separately in Table 3, we find that, even though physical appearance is regarded as being very important in the dressy occupation (see

Figure 1 Panel B), the average looking earn more than those with above average looks. The average looking also earn more than the beautiful in the non-dressy category. The results are statistically significant only for women in the dressy profession.

In other words, raw wages indicate that there exists a beauty penalty for women and men and a beauty premium for below average looking men. When we confine this to occupations we find a significant beauty penalty for women in the dressy occupation and a beauty penalty for men in the non-dressy profession.

Naturally, it may be the case that average looking individuals are better qualified or have other desirable human capital traits and this is the main reason they obtain a higher wage.[3] We suggest a number of techniques in the next section to control for this.

5 Empirical Results

In the first instance, we examine the determinants of earnings and check for selection in our model. Next, we test the Hammermesh and Biddle model also across the distribution with the use of quantiles regressions. Finally, we use DR techniques to identify the "characteristic" and "coefficient" gaps.

5.1 Determinants of earnings

Table 4 and 5 include the selection model and quantile regression model results for women and men. Firstly, looking at the estimation results of the selection equation in column (2), we see that married women are less likely to work. Age has the traditional positive effect on work for both sexes at a decreasing rate and the number of children has a negative effect on the labor supply of women only. ρ is not significantly different for zero and the low χ^2 suggests that there is no correlation across the selection probit and wage equation, suggesting that we do not need to worry about having biased estimates if we do not control for selection. As a check, we have also included a model without selection in the first column. We find the coefficients to be almost identical in both models and the R^2 is 0.57 for women and 0.63 for men in the models without selection correction.

When we look at the direct effects of covariates in the wage equation, we find that mar-

[3]Tables A2 and A3 indicate the average looking have significantly higher rates of college education, they are more likely to work at a big company and as a civil servant. All these factors are positively related to wages.

ital status has no significant effect on women's wages (only on the decision to work). High education, experience, working for a big company and being a civil servant have the expected positive effects whereas having a temporary work contract has a diminishing effect on wages.[4] In a trend specific to Luxembourg, working part-time has a positive effect on hourly wages (particularly for women), although this positive effect is concentrated in the higher quantile groups.[5] Both male and female Portuguese immigrants and other non-natives have a disadvantage in the labor market.[6]

5.2 Beauty, Beast or just Average Jo(e)?

In this section, we employ the Hamermesh and Biddle (1994) model with and without selection correction, and apply quantile regression and DR to disentangle the relationship between beauty and earnings.

As discussed in Section 4 and Table 2, raw differences indicate that there exists a wage penalty for those with above average looks. When we control for demographic and labor market characteristics, we still find this to be the case. Recall that the Hamermesh and Biddle (1994) model identifies three possible sources of looks-related discrimination: productivity via customer discrimination, employer discrimination and occupational crowding. In Table 4 we find a penalty of about 10% for women with above average looks. The effect is confirmed at several points in the distribution including the 25^{th}, 50^{th} and 90^{th} percentiles for women. Although we do not find a significant average effect for women with below average looks, we do find an 8% penalty for being under average looking in the first quartile group and at the median, indicating that there is variation in the effects across the distribution and that the average effect is hiding more detailed information. For men, we find no significant effect for above or below average looking men (table 5). In the Hamermesh and Biddle (1994) model, this would suggest that employer discrimination exists at some points in the distribution for women and, in most cases, employers favor average looking people rather than bad or good looking people.

[4]In many European countries, including Luxembourg, initially individuals are offered temporary contracts (1, 2 or 3 years renewable, but up to 5 years) at a company. After this period they have to be offered permanent contracts.

[5]Luxembourg's labor market differs from the US market. The financial sector accounts for around $2/3$ of economic activity and contract work and independent consultancies are common in this sector. This can lead to working weeks under 40 hours but with high salaries. In addition, full-time workers aged 57 or over have the option scaling back to part-time work and receiving a partial pension. This may be causing a positive effect on the part-time variable, especially for higher earners.

[6]Over 40% of the population in Luxembourg is foreign born with 16.2% being born in Portugal. The immigrant population is an interesting mix of either very low or very high qualified individuals. For a comparative perspective of immigrants in Luxembourg see Mathä et al. (2011)

Customer discrimination suggests that, in some occupations (where looks matter), looks will enhance productivity through consumer discrimination. In our model this effect is seen in the coefficients on the interaction terms between beauty and 'dressy' occupations (our β_4 from (3). We find no statistically significant evidence of this in either our selection equation or in our quantile regressions for women. We do find a beauty premium for men at the top of the distribution for the good looking and a premium for the below average looking at the median.

Finally, we examine the occupational crowding hypothesis, according to which, an occupational requirement for beauty will create independent effects on wages and will lead people to select certain occupations based on looks and their expected returns to these looks (our β_3). This is confirmed as the coefficient on the dressy variable is positive and significant for all our specifications for women and for men (except the 1^st quantile). We do find variation in the effect throughout the 5 quantile groups, particularly for men. The effect is three times stronger at the top of the distribution at 23% in the top quantile group, compared to 7% in the 1^{st} quantile group.

5.3 Characteristics or unexplained gaps?

The previous subsection clearly shows that there are variations in the effect of physical appearance throughout the wage distribution so, in the final stage of the analysis, we turn to DR results.

We plot the predicted distribution of wages for each class of physical appearance against the actual distribution and find an excellent fit for our model (see Figure A2 in the Appendix). We graphically represent the coefficient and characteristic effects for the distribution of male and female wages by class of physical appearance using the decomposition elaborated in equation (8). Statistical significance may be inferred from the 95% confidence intervals shown.[7]

Looking firstly at the decomposition of wage gaps for the above average compared to average looking men and women in Figure 2, we see that there is a penalty of around $5ppt$ to being above average looking compared to average looking for women at the bottom of the wage distribution. This, however, is not statistically significant. There is no coefficient effect further up in the distribution (confirmed in Table 4). Men experience a similar penalty around the bottom quartile of the distribution, which is statistically significant. In

[7]The confidence intervals are constructed using the point estimates +/- 1.96 standard deviations calculated from 250 draws at the individual level.

contrast, the characteristics gaps for both women and men are large and highly significant, particularly toward the bottom half of the distribution, indicating that average looking people have better characteristics than above average looking people, and that this is the driving reason for the raw wage gaps between these groups. This is particularly true for women.

Turning to the decomposition of the wage gap between average looking people and under average looking people in Figure 3, we find that the characteristic effect is still dominant and that average looking people have better labor market characteristics than under average looking people, particularly at the bottom of the wage distribution. There is also a consistent coefficient effect for women of between $5 - 8ppt$ in the lower half of the distribution. There is no significant coefficient effect for men.

A comparison between the quantile regressions and the distribution regression shows a couple of interesting things. Firstly, the beauty penalty for above average looking women observed in the quantile regression framework all but disappears once we employ the distribution regression approach. It was therefore likely to have been a manifestation of the fact that average looking women have better characteristics than above average looking women, allowing them to compete for higher wages and this was not fully picked up by the dummy variables in the quantile regression specification. Allowing different returns to characteristics for each physical appearance group across the entire distribution of wages renders these effects insignificant for the most part and the only penalty identified is against below average looking women, earning below average wages. This effect could be the result of either customer or employer discrimination. As our distribution regression model does not allow us to differentiate between these, we must rely on the quantile regression framework for inference which suggests that it is employer discrimination.

6 Additional results

6.1 The dressy profession

Our framework suggested the existence of occupational sorting whereby looks could enhance productivity and yield a positive effect on wages. To check the robustness of our results and to complement the above, we present results from some additional specifications. Using the distribution regression framework, we rerun our analysis, retaining only those who work in a "dressy" profession. As seen in Table A2 and A3, individuals with below or above average physical appearance also have less desirable labor market characteristics. If sorting occurs, individuals with less desirable physical appearance characteristics but higher other labor market attributes and those with desirable physical appearance characteristics but lower other labor market attributes can be expected to sort into "dressy" professions. If this occurs, we expect the characteristics gap to be muted. Whether sorting occurs or not, we expect a higher coefficient gap in the dressy profession. In line with our results from the QR framework, we find evidence of occupational sorting, particularly for below average looking individuals. The model for all professions combined in Figure 2 and 3 shows a large characteristic effect for both men and women, indicating that average looking people have more desirable labor market characteristics on average. Restricting the sample to those in the dressy profession (Figures 4 and 5), we see that there is no characteristic effect for men and a much smaller one for women, indicating that one of two things is happening. Either, there are relatively more ill qualified average looking people or highly qualified below average looking people. Whichever is the case, there is distinct evidence of occupational sorting.

The coefficient effect for below average looking women in the dressy profession is higher, at around $7-12ppt$. There is also a penalty of $5-9ppt$ for above average women in the lower quartile group. For men, we find a premium of $5ppt$ for being unattractive at the very top of the wage distribution and a premium of $5-7ppt$ for being attractive in the top half of the distribution.

6.2 A younger cohort

We also perform further analysis by restricting the sample to young (25-45 year olds) people, whose physical appearance may be more important in the labor market. A preliminary QR analysis (results available upon request) reconfirms a (stronger) penalty for below average looking young women in the middle of the distribution and shows a penalty for being above average looking only for the top of the female wage distribution. For men, QR shows a new penalty for above average looking younger men towards the top of the wage distribution. The difficulty with the QR results is that we do not know the wage rate at which these penalties occur and whether the results are comparable to the overall sample. The DR results make this task much easier as individuals are compared at wage rates rather than quantile groups, which can change by subgroup. Figure 6 shows no evidence of a significant premium or penalty for being attractive for either men or women in this group. It does show a large characteristic gap indicating that younger average looking individuals have better wage enhancing characteristics than above average looking individuals, particularly women.[8] The DR results in Figure 7 reconfirm a significant penalty for below average looking women in the middle of the distribution. There is also a large coefficient gap comparable to that observed using the larger age sample. There is still no significant coefficient gap for below average men and the characteristic gap is very small.

7 Conclusions

Using various techniques, we show that the effect of beauty varies across the distribution and that mean techniques can provide misleading information due to the canceling out of opposite effects. Using quantile and distribution regression we find a penalty for unattractive women in the lower half of the distribution. This result is confirmed when we restrict our sample to both a younger cohort and those women working in the dressy profession. For men, there is no consistent penalty or premium for physical appearance, except in the dressy profession. Here, we see a beauty premium for men in the top half of the distribution. Restricting the sample in this way, we also find evidence of occupational sorting, particularly for unattractive women and men. By constructing counterfactual distributions using DR, we find that much of the wage penalties observed in the Hamermesh and Biddle (1994) model are due to the different characteristics of people in different physical appearance classes, and only a small portion may actually be attributed to discrimination. The DR method, which is largely unused in this literature, provides a straight forward manner to examine and decompose the effect of explanatory variables on an outcome variable, if we suspect the effect varies across the distribution.

[8] In terms of probabilities this means that above average looking women have a higher probability of earning lower wages compared to average women if they are paid as average looking women.

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8 Tables and Figures

Table 1: A comparison of beauty ranks and importance of beauty means between women and men and by occupation.

Panel A	Women	Men	diff
Share in each category:			
above	0.317	0.343	-0.025
average	0.409	0.394	0.016
below	0.273	0.264	0.009
Perceived importance of beauty by:			
all	1.970	1.834	0.135***
above	2.022	1.894	0.129***
average	1.925	1.821	0.105***
under	1.974	1.775	0.198***
Dressy:			
above	2.099	1.936	0.163***
average	1.975	1.828	0.147***
below	2.014	1.809	0.205***
Non-dressy:			
above	1.809	1.836	-0.027
average	1.691	1.807	-0.116
below	1.890	1.742	0.148*

Panel B	Non-dressy	Dressy	diff
Perceived importance of beauty:			
All	1.799	1.939	-0.140***
Women	1.804	2.023	-0.219***
Men	1.797	1.861	-0.064*
Beauty ranks:			
All	2.015	2.091	-0.076***
Women	1.982	2.065	-0.083*
Men	2.029	2.115	-0.085**

Source: 2007 PSELL3; t statistics in parentheses * p<0.1 ** p<0.05 *** p<0.01

Note: Beauty scale: 1 - below average; 2 - average; 3 - above average.

Table 2: Select wage differences statistics for various beauty categories (in Euros).

	Above	Average	diff
All	15.052	16.789	-1.736***
Women	13.829	16.077	-2.248***
Men	15.873	17.325	-1.452***

	Average	Under	diff
All	16.789	15.565	1.223**
Women	16.077	14.686	1.390
Men	17.325	16.224	1.101*

	Above	Under	diff
All	15.052	15.565	-0.513
Women	13.829	14.686	-0.858
Men	15.873	16.224	-0.351

Source: 2007 PSELL3; t statistics in parentheses * p<0.1 ** p<0.05 *** p<0.01

Table 3: Select wage differences statistics for various beauty categories (in Euros).

	Above	Average	diff
Women: Dressy	15.843	17.720	-1.877***
Men: Dressy	19.995	20.923	-0.928
Women: Non-dressy	8.312	8.945	-0.633
Men: Non-dressy	10.313	10.932	-0.620

	Average	Under	diff
Women: Dressy	17.720	17.366	0.354
Men: Dressy	20.923	21.283	-0.360
Women: Non-dressy	8.945	9.174	-0.229
Men: Non-dressy	10.932	11.287	-0.354

	Above	Under	diff
Women: Dressy	15.843	17.366	-1.524
Men: Dressy	19.995	21.283	-1.288
Women: Non-dressy	8.312	9.174	-0.862
Men: Non-dressy	10.313	11.287	-0.974***

Source: 2007 PSELL3; t statistics in parentheses * p<0.1 ** p<0.05 *** p<0.01

Table 4: OLS, selection model and quantile regressions (women).

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
	OLS	lnhr	work	q10	q25	q50	q75	q90
under_avg	-0.07	-0.07		-0.04	-0.08**	-0.08**	-0.05	-0.10
under*dressy	-0.02	-0.02		-0.05	-0.03	0.00	0.00	0.02
above_avg	-0.10**	-0.10**		-0.11	-0.11***	-0.10**	-0.07	-0.13*
above*dressy	0.09	0.09		0.06	0.05	0.09	0.09	0.11
dressy	0.15***	0.15***		0.11	0.12***	0.17***	0.19***	0.19**
married	0.00	-0.00	-0.52***	0.04	0.04	0.03	0.02	0.04
lt high school	-0.14***	-0.14***		-0.06	-0.10***	-0.11***	-0.18***	-0.21***
college	0.42***	0.42***		0.27***	0.36***	0.39***	0.38***	0.38***
experience	0.02***	0.02***		0.02***	0.02***	0.02***	0.03***	0.02***
experience2	-0.00*	-0.00*		-0.00*	-0.00**	-0.00	-0.00**	-0.00
part-time	0.16***	0.16***		-0.00	0.02	0.11***	0.23***	0.24***
big company	0.13***	0.13***		0.10***	0.11***	0.11***	0.11***	0.12***
temporary	-0.13*	-0.13*		-0.30***	-0.21***	-0.16***	-0.08	-0.03
civil servant	0.34***	0.34***		0.46***	0.40***	0.40***	0.34***	0.38***
Portugese	-0.16***	-0.15***	0.57***	-0.18***	-0.22***	-0.22***	-0.25***	-0.27***
other non-native	-0.14***	-0.14***	0.11	-0.17***	-0.16***	-0.15***	-0.11***	-0.07*
bad health	0.04	0.03	-0.47**	-0.10	-0.07	-0.10	0.01	-0.02
age			0.34***					
age2			-0.42***					
No. children			-0.27***					
child			-0.03					
proxy			-0.04					
Constant	2.24***	2.22***	-5.48***	2.03***	2.18***	2.27***	2.38***	2.56***
λ		0.02						
ρ		0.05						
σ		0.36***						
Wald test (χ^2)		0.22						
Pseudo-R^2	0.57			0,218	0,335	0,410	0,414	0,413
Observations	1,543	2,903	2,903	1,543	1,543	1,543	1,543	1,543

Source: 2007 PSELL3; Robust standard errors used. Bootstrapped standard errors for quantile regressions (200 reps).

t statistics in parentheses * p<0.1 ** p<0.05 *** p<0.01

Note: We drop observations with wage=0

Table 5: OLS, selection model and quantile regressions (men).

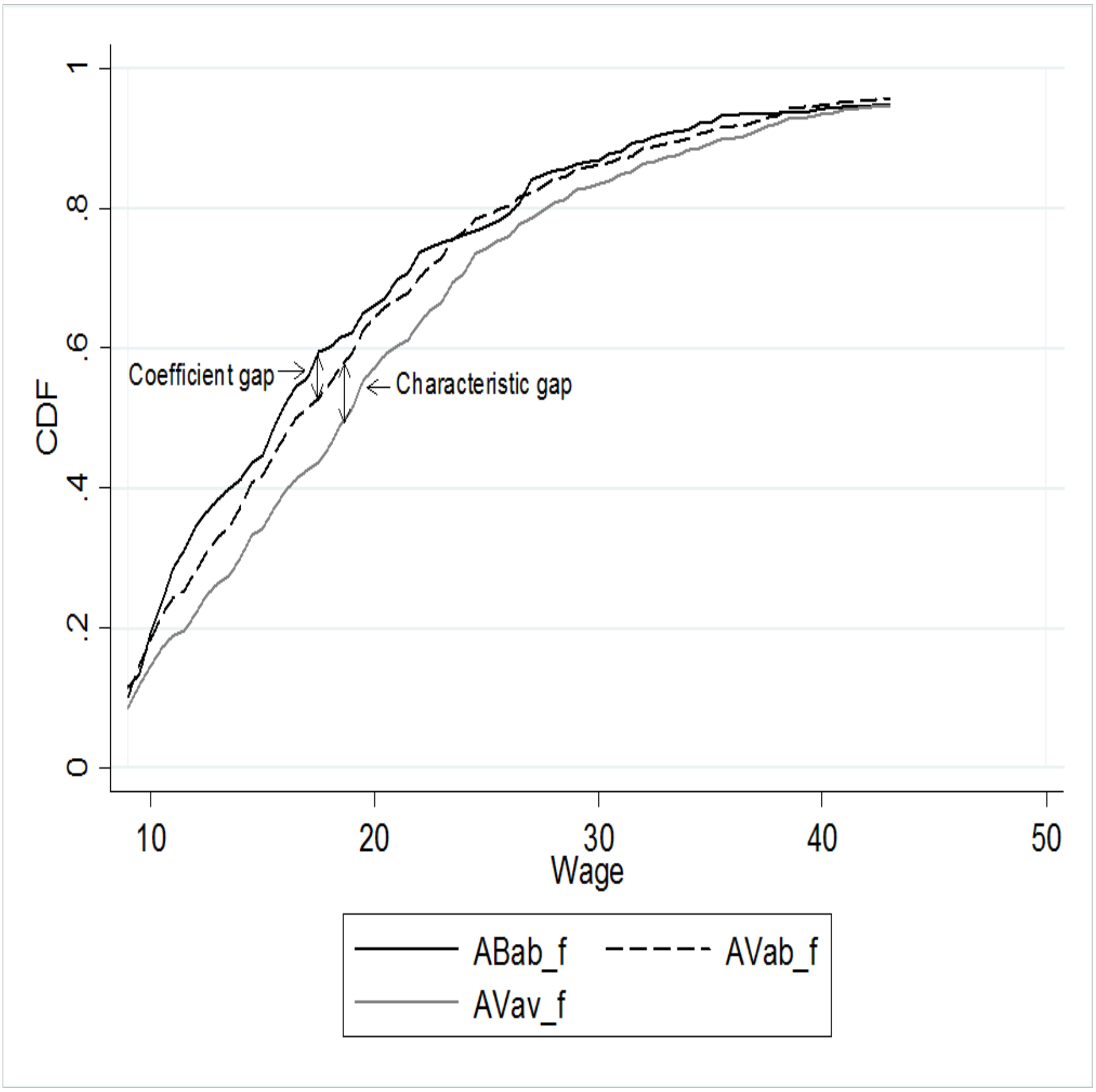
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
	OLS	lnhr	work	q10	q25	q50	q75	q90
under_avg	0.03	0.03		0.02	0.03	-0.01	-0.01	-0.03
under*dressy	-0.02	-0.02		-0.08	-0.03	0.07*	0.06	0.07
above_avg	-0.01	-0.01		-0.00	-0.00	-0.01	-0.04	-0.01
above*dressy	0.03	0.03		-0.04	-0.01	0.00	0.07*	0.02
dressy	0.21***	0.21***		0.07	0.10***	0.15***	0.19***	0.23***
married	0.06*	0.06*	0.18	0.09***	0.08***	0.09***	0.08***	0.09***
lt high school	-0.19***	-0.19***		-0.05*	-0.11***	-0.14***	-0.15***	-0.19***
college	0.36***	0.36***		0.43***	0.43***	0.45***	0.39***	0.42***
experience	0.03***	0.04***		0.02***	0.02***	0.03***	0.03***	0.03***
experience2	-0.00***	-0.00***		-0.00	-0.00***	-0.00***	-0.00***	-0.00***
part-time	0.30***	0.30***		-0.35*	0.09	0.23**	0.43***	0.54***
big company	0.16***	0.16***		0.12***	0.13***	0.10***	0.10***	0.05*
temporary	-0.19***	-0.19***		-0.24***	-0.19***	-0.09**	-0.10***	-0.09*
civil servant	0.27***	0.27***		0.45***	0.36***	0.26***	0.21***	0.17***
Portugese	-0.21***	-0.21***	0.49***	-0.19***	-0.25***	-0.25***	-0.27***	-0.27***
other non-native	-0.12***	-0.12***	0.00	-0.18***	-0.20***	-0.20***	-0.10***	-0.04
bad health	-0.11*	-0.12	-1.84***	-0.11	-0.11*	-0.19***	-0.19***	-0.23***
age			0.49***					
age2			-0.62***					
noch			-0.05					
child			0.19					
proxy			0.14					
Constant	2.24***	2.24***	-8.05***	2.08***	2.21***	2.34***	2.47***	2.69***
λ		0.01						
ρ		0.18						
σ		-0.33***						
Wald test (χ^2)		0.01						
Pseudo-R^2	0.63			0.257	0.376	0.443	0.454	0.452
Observations	2,127	2,782	2,782	2,127	2,127	2,127	2,127	2,127

Source: 2007 PSELL3; Robust standard errors used. Bootstrapped standard errors for quantile regressions (200 reps).

t statistics in parentheses * p<0.1 ** p<0.05 *** p<0.01

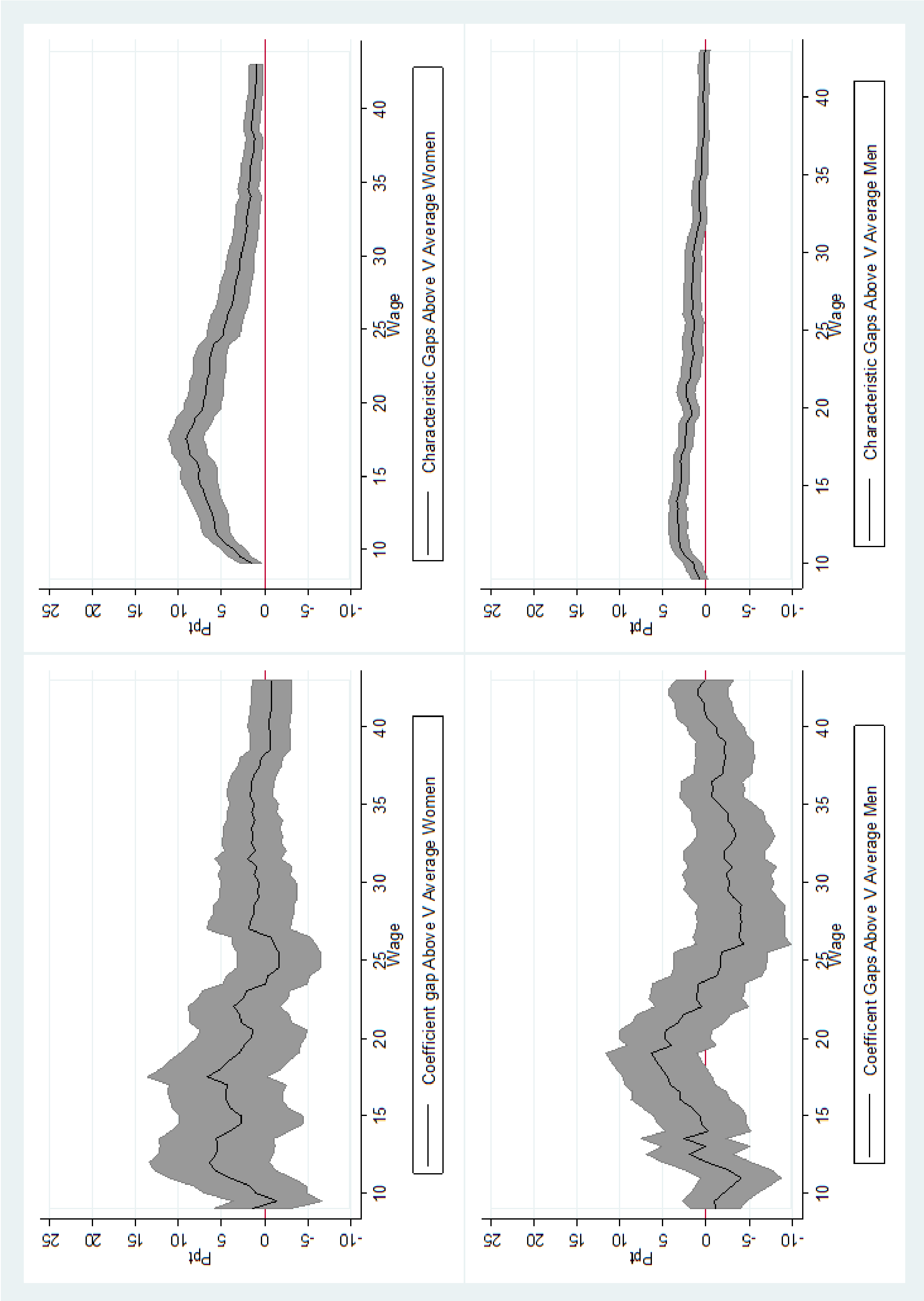
Note: We drop observations with wage=0

Figure 1 Cumulative distribution function and counterfactual CDF for above average and average women.



Source: 2007 PSELL3
Note: Wage distribution for reported looks: $ABab$- above average; $AVav$- average; $AVab$- above average paid as average
$ABab - AVab$ coefficient gap; $AVab - AVav$ characteristic gap

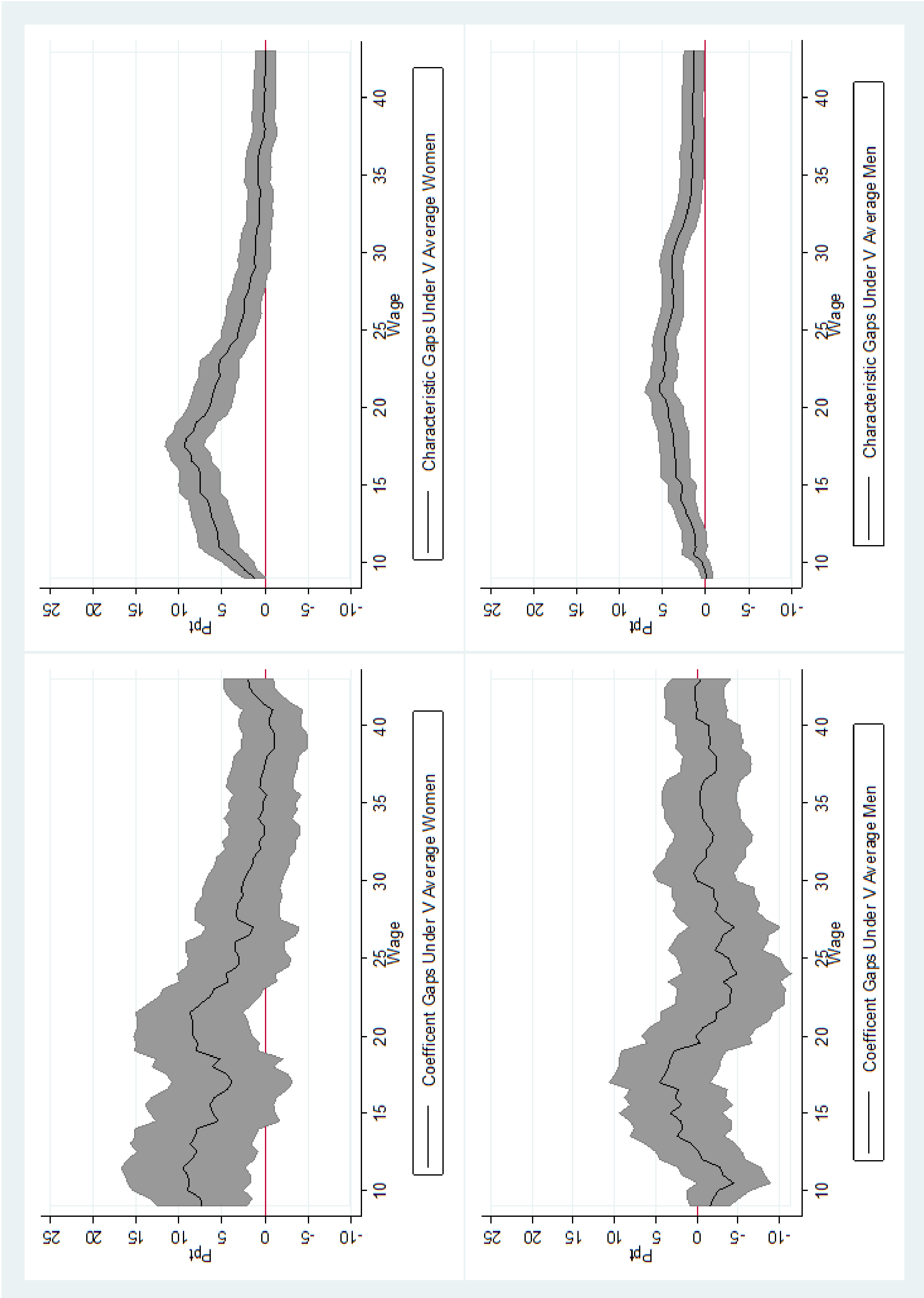
Figure 2 Coefficient and characteristics gaps for above average vs. average women and men.



Source: 2007 PSELL3

Note: Wage distribution for reported looks: $ABab$- above average; $AVav$- average; $AVab$- above average paid as average. Gap > 0 indicates a higher probability of lower wages for the above average group. $ABab - AVab$ coefficient gap; $AVab - AVav$ characteristic gap

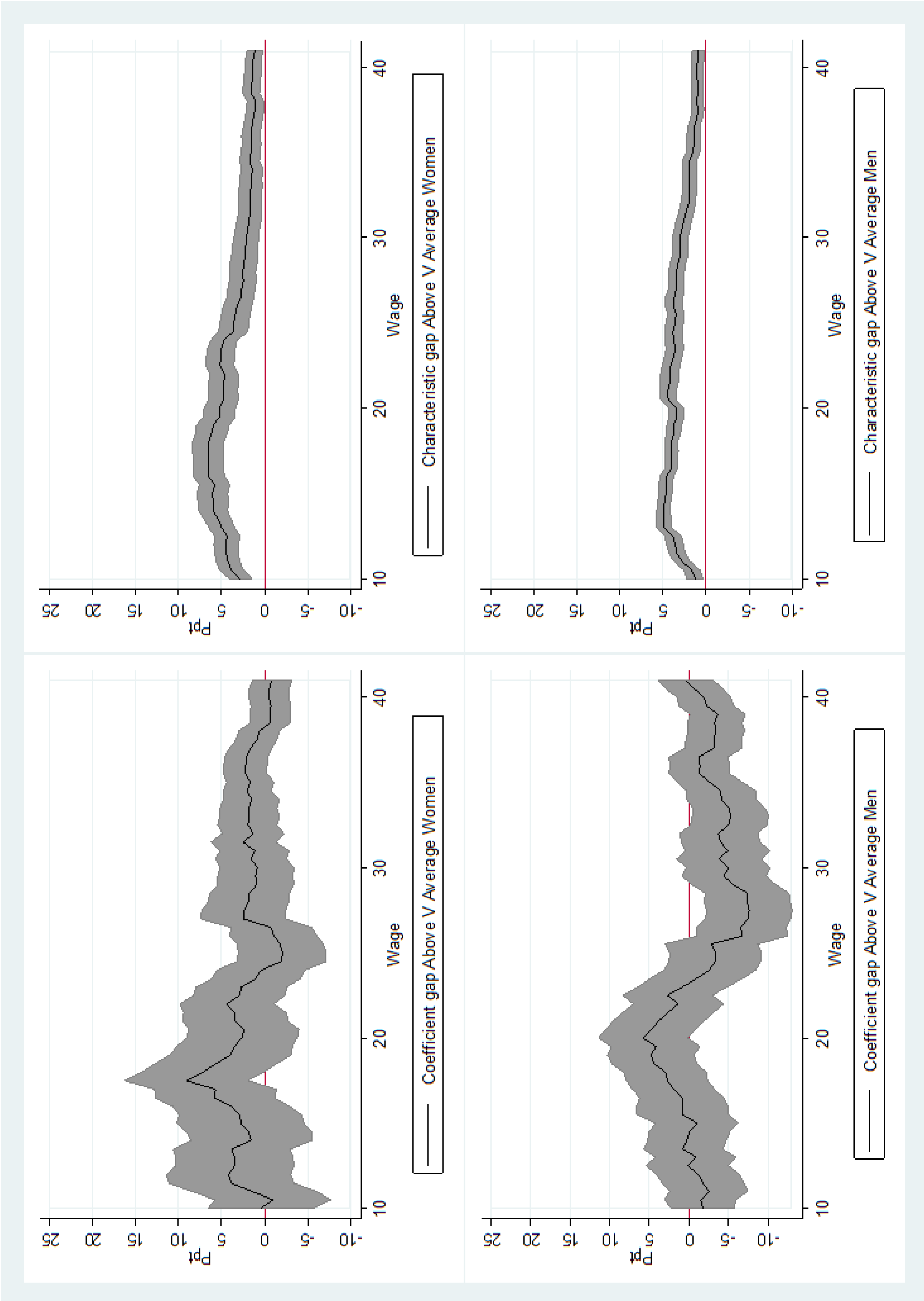
Figure 3 Coefficient and characteristics gaps for under average vs. average women and men.



Source: 2007 PSELL3

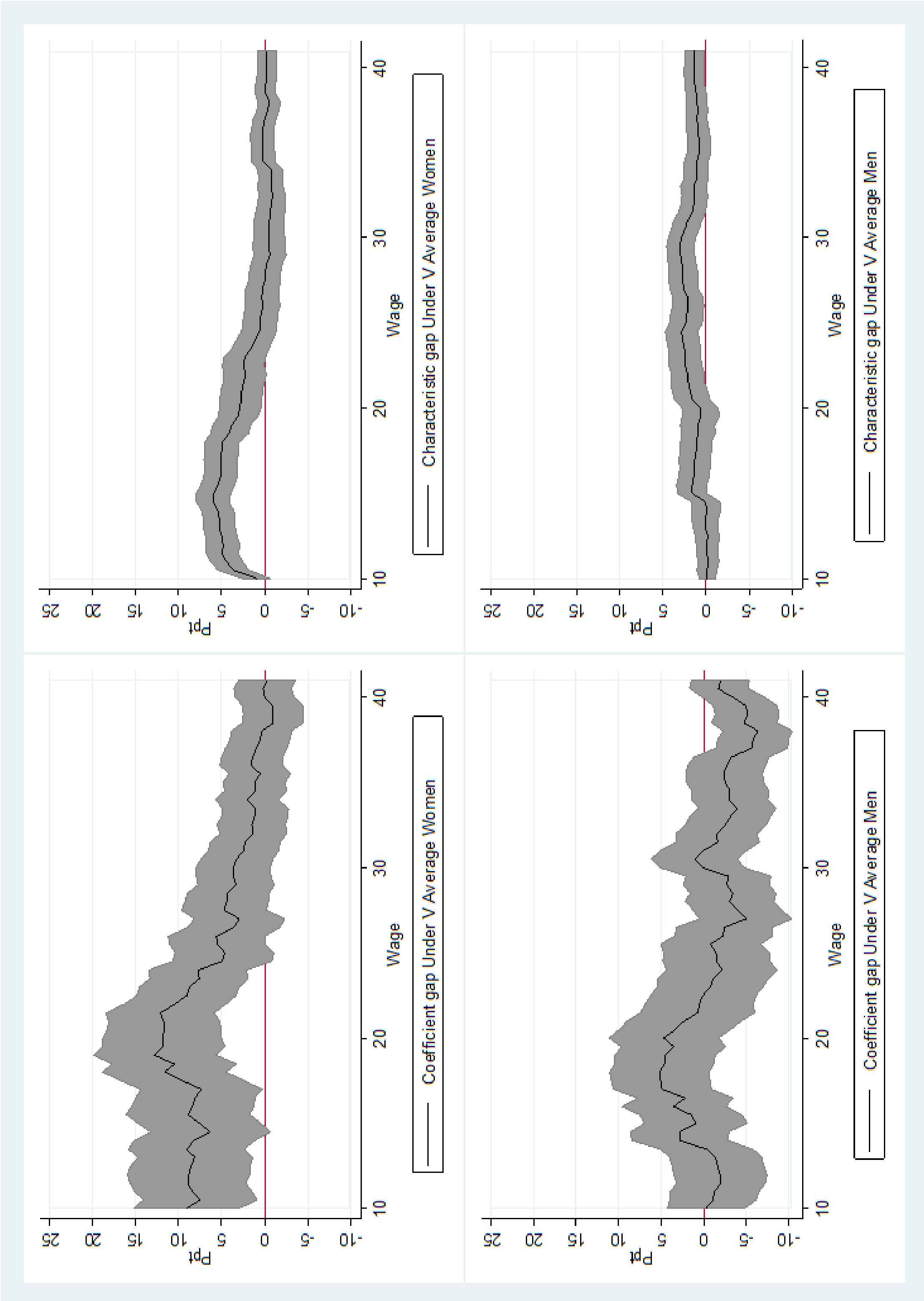
Note: Wage distribution for reported looks: $UNun$- under average; $AVav$- average; $AVun$- under average paid as average. Gap > 0 indicates a higher probability of lower wages for the under average group. $UNun - AVun$ - coefficient gap; $AVun - AVav$ - characteristic gap

Figure 4 Coefficient and characteristics gaps for above average vs. average women and men in the dressy profession.



Source: 2007 PSELL3
Note:Wage distribution for reported looks: $ABab$- above average; $AVav$- average; $AVab$- above average paid as average. Gap > 0 indicates a higher probability of lower wages for the above average group. $ABab - AVab$ coefficient gap; $AVab - AVav$ characteristic gap

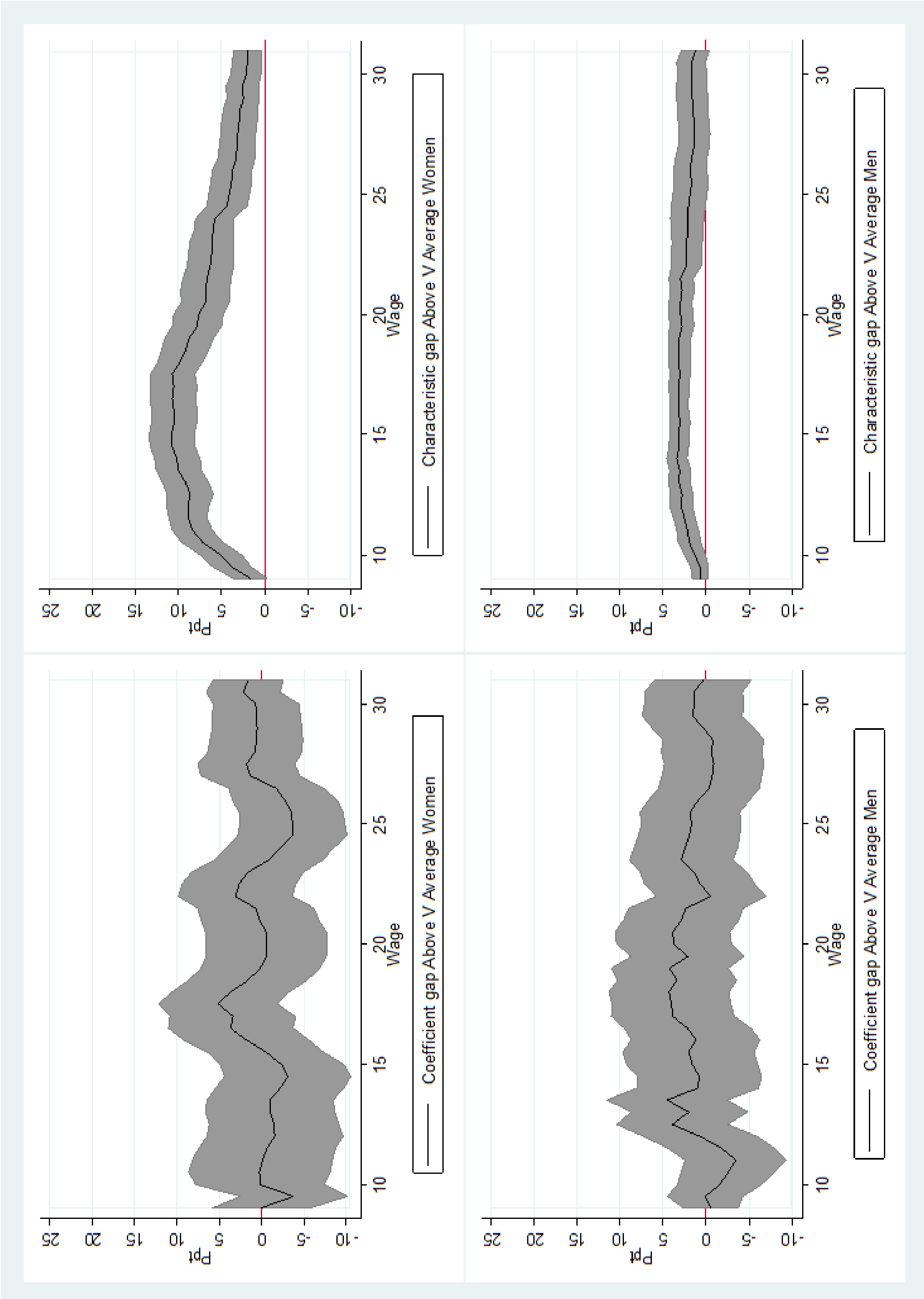
Figure 5 Coefficient and characteristics gaps for under average vs. average women and men in the dressy profession.



Source: 2007 PSELL3

Note: Wage distribution for reported looks: $UNun$- under average; $AVav$- average; $AVun$- under average paid as average. Gap > 0 indicates a higher probability of lower wages for the under average group. $UNun - AVun$ coefficient gap; $AVun - AVav$ characteristic gap

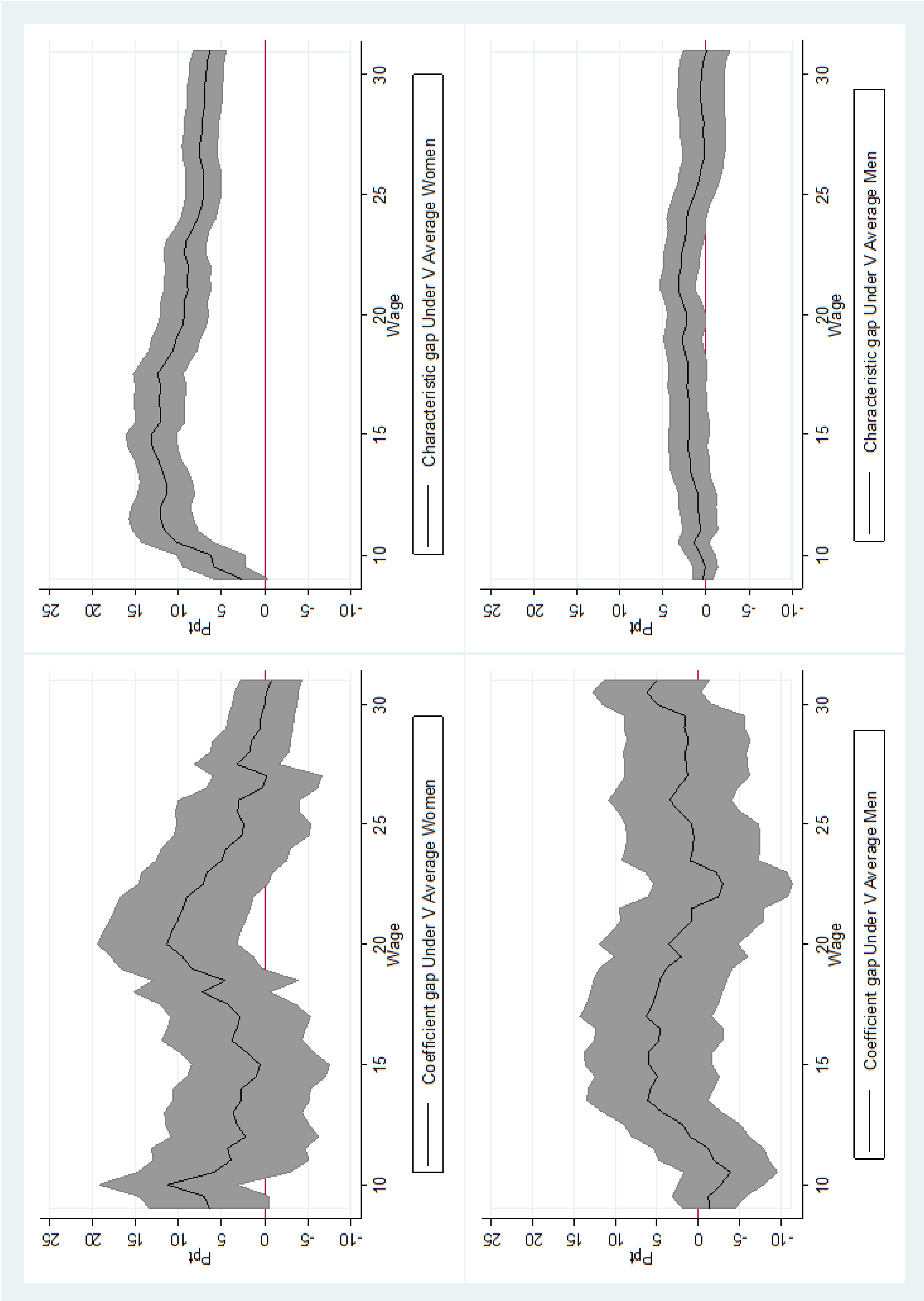
Figure 6 Coefficient and characteristics gaps for above average vs. average women and men between 25-45 years of age.



Source: 2007 PSELL3

Note: Wage distribution for reported looks: $ABab$- above average; $AVav$- average; $AVab$- above average paid as average. Gap > 0 indicates a higher probability of lower wages for the above average group. $ABab - AVab$ coefficient gap; $AVab - AVav$ characteristic gap

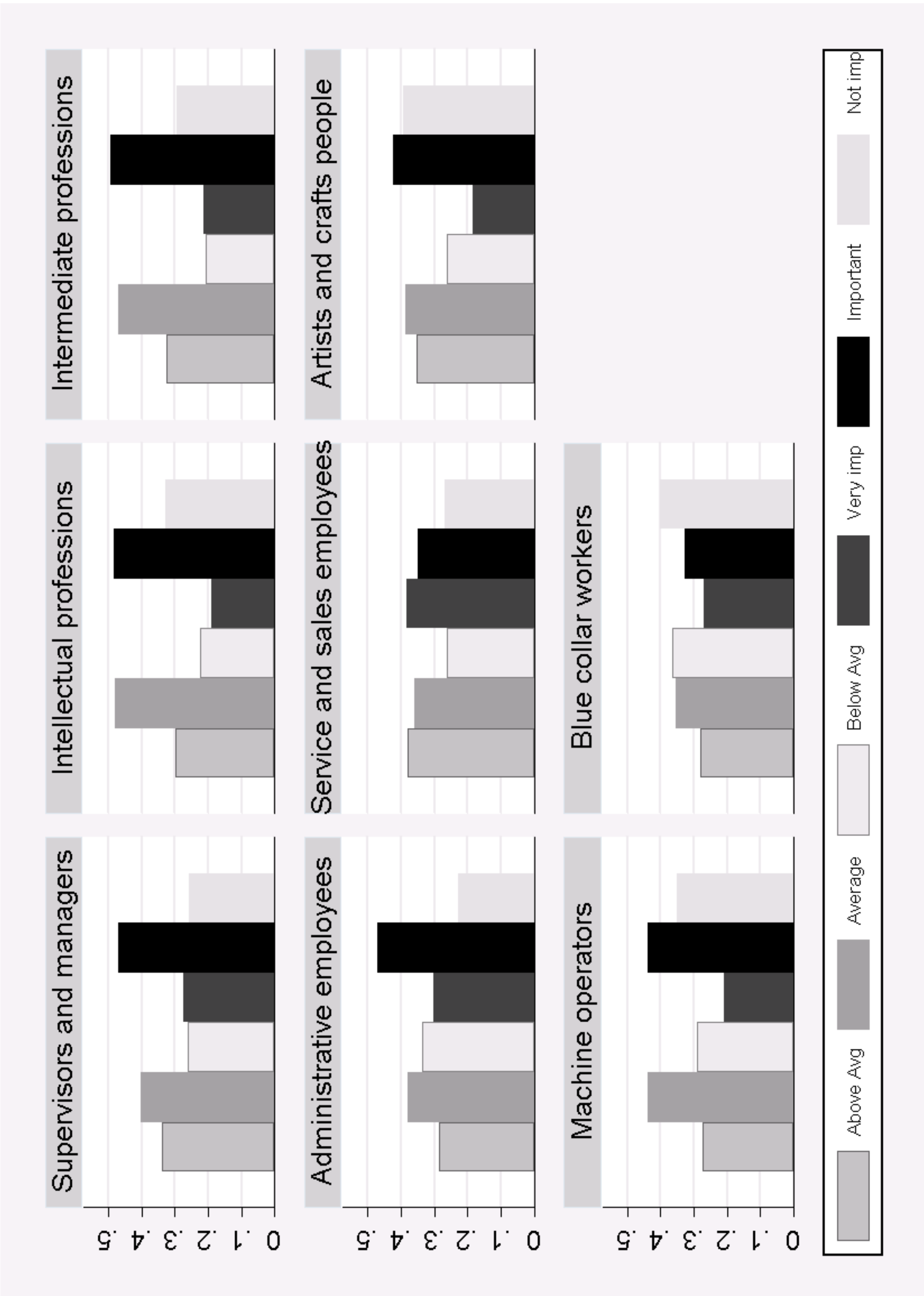
Figure 7 Coefficient and characteristics gaps for under average vs. average women and men between 25-45 years of age.



Source: 2007 PSELL3

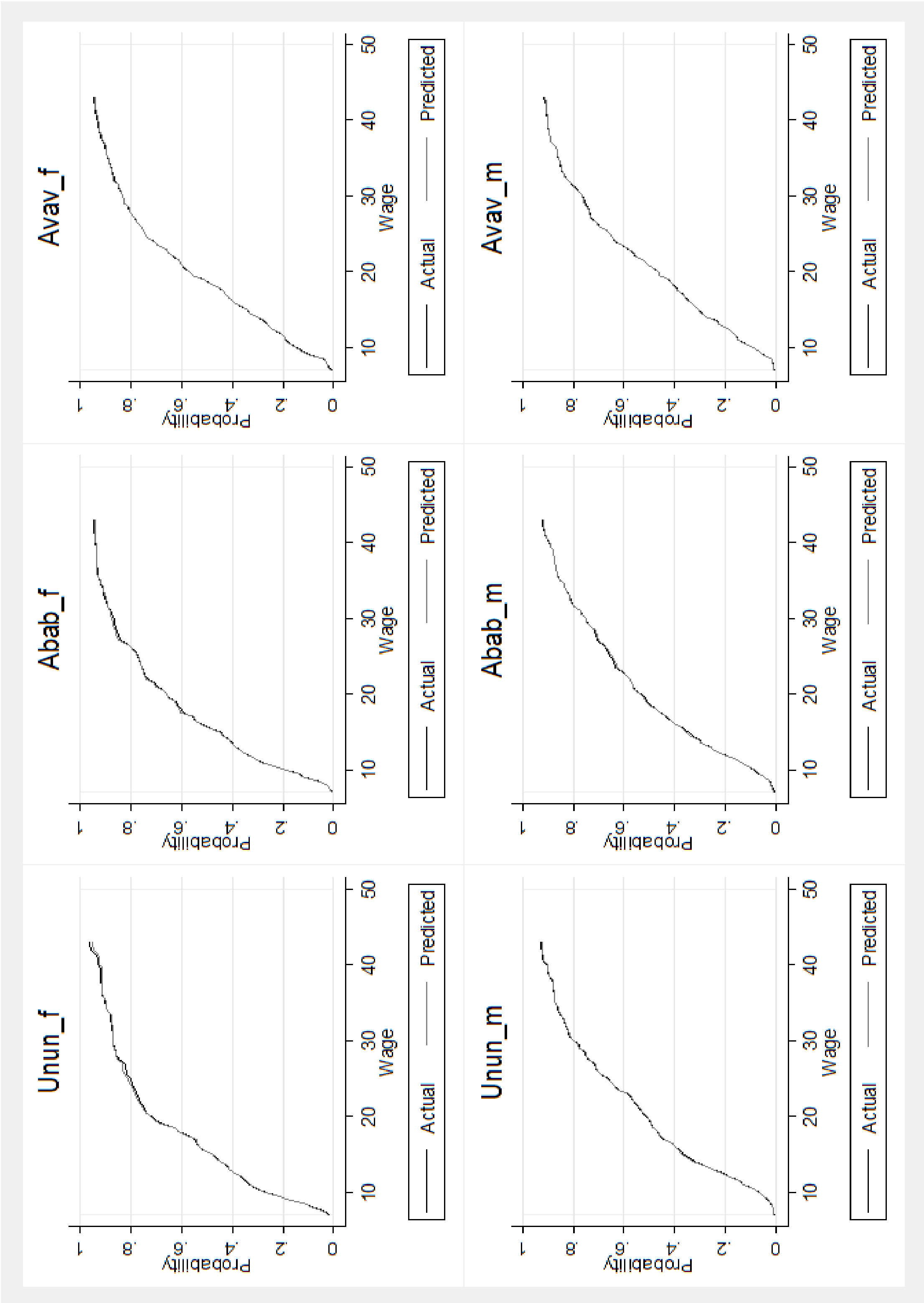
Note: Wage distribution for reported looks: $UNun$- under average; $AVav$- average; $AVun$- under average paid as average. Gap > 0 indicates a higher probability of lower wages for the under average group. $UNun - AVun$ coefficient gap; $AVun - AVav$ characteristic gap

Figure A1 Self-assessed beauty by occupation (in percentages).



Source: 2007 PSELL3

Figure A2 Goodness of fit of the distribution regressions.



Source: 2007 PSELL3

Table A1: Explanatory variables used for estimation.

married	1 if married
lt high school	1 if highest education received is first cycle of highschool
college	1 if highest education received is third level
experience	self-reported number of years working
part-time	1 if work < 30hours per week
big company	1 if > 50 employees at workplace
temporary	1 if temporary contract
civil servant	1 if public sector employee
Portugese	1 if portuguese nationality
other-non-native	1 if nationality other than portuguese/luxembourgish
bad health	1 if classify health as bad/very bad
age	age in years
no. children	number of children the individual has
child	1 if the individual has children
proxy	1 if the individual did not answer the questionnaire themselves
below_avg	self-reported physical appearance of 1-5 out of 10
above_avg	self reported physical appearance of 8-10 out of 10
dressy	1 if the individual works in a "dressy" profession

Source: 2007 PSELL3/EU-SILC

Table A2: Select statistics for above average, average and under average beauty (women)

	(1)	(2)	(3)	(4)	(5)
	Above	Average	Under	(1)-(2) diff	(2)-(3) diff
age	36.409	37.367	38.327	-0.958	-0.960
married	0.549	0.556	0.548	-0.007	0.008
single	0.309	0.317	0.302	-0.008	0.016
separated	0.142	0.127	0.151	0.015	-0.024
no. children	1.210	1.150	1.357	0.059	-0.207***
children (0/1)	0.643	0.641	0.682	0.002	-0.041
lt high school	0.371	0.249	0.422	0.122***	-0.173***
high school	0.285	0.302	0.332	-0.016	-0.030
college	0.333	0.437	0.232	-0.103***	0.205***
work experience	14.607	14.980	16.599	-0.373	-1.619**
full-time	0.727	0.669	0.664	0.058**	0.005
part-time	0.323	0.390	0.392	-0.067**	-0.002
big company	0.397	0.497	0.455	-0.100***	0.042
temporary	0.126	0.093	0.107	0.033*	-0.014
civil servant	0.192	0.257	0.206	-0.065***	0.050*
native	0.355	0.401	0.404	-0.046	-0.003
Portugese	0.242	0.166	0.346	0.076***	-0.180***
other non-native	0.403	0.433	0.251	-0.030	0.183***
bad health	0.042	0.023	0.044	0.019*	-0.021*
great health	0.417	0.409	0.288	0.008	0.121***
Occupation type: Dressy	0.733	0.813	0.673	-0.080***	0.140***
Observations	501	646	431	Total	1578

Source: 2007 PSELL3; t statistics in parentheses * p<0.1 ** p<0.05 *** p<0.01

Table A3: Select statistics for above average and average beauty (men)

	(1)	(2)	(3)	(4)	(5)
	Above	Average	Under	(1)-(2) diff	(2)-(3) diff
age	37.193	38.029	39.400	-0.836	-1.371**
married	0.609	0.597	0.637	0.012	-0.040
single	0.321	0.326	0.259	-0.005	0.067***
separated	0.070	0.077	0.104	-0.007	–0.027*
no. children	1.277	1.191	1.428	0.086	–0.237***
children (0/1)	0.641	0.608	0.697	0.033	-0.089***
lt high school	0.347	0.307	0.440	0.040*	-0.133***
high school	0.352	0.315	0.317	0.037	-.002
college	0.297	0.373	0.231	-0.076***	0.142***
work experience	17.525	17.809	20.880	-0.284	-3.071***
full-time	0.983	0.977	0.977	0.006	-0.001
part-time	0.031	0.040	0.037	-0.009	0.003
big company	0.499	0.590	0.581	-0.090***	0.009
temporary	0.116	0.086	0.096	0.030**	-0.009
civil servant	0.171	0.210	0.150	-0.038*	0.060***
native	0.348	0.395	0.350	-0.047*	0.046*
Portugese	0.285	0.217	0.374	0.068***	-0.157***
other non-native	0.367	0.388	0.277	-0.021	0.112***
bad health	0.013	0.017	0.050	-0.004	-0.033***
great health	0.444	0.407	0.306	0.038	0.101***
Occupation type: Dressy	0.574	0.640	0.494	-0.066***	0.146***
Observations	747	858	575	Total	2180

Source: 2007 PSELL3; t statistics in parentheses * p<0.1 ** p<0.05 *** p<0.01

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