Physical Attractiveness, Employment and Earnings

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Abstract

This study attempts to replicate the work of Pfeifer (2012) using a different sample from the German survey ALLBUS 2008, in order to examine the relationships between physical attractiveness, employment and earnings. It finds that some of the conclusions of the previous study hold: (1) In the employment status model, the estimates of two specifications are almost identical, while the marginal effect of physical attractiveness rated by interviewers at the end of the interview is greater than that at the start. (2) In the linear earnings models, physical attractiveness rated by interviewers at the end can explain the variance of earnings better than physical attractiveness rated by the interviewers at the start of the interview, and the estimated coefficients of attractiveness are larger for men than for women. (3) In the non-linear models, it is confirmed that the wage punishment for below-average attractiveness is more serious than the wage premium for above-average attractiveness. Additionally, there are two notable innovations in the approach of this paper. One innovation is the calculation of marginal effects at representative values of attractiveness, and the other is the calculation of the turning points of physical attractiveness for the OLS regression models.

1．Introduction

“What is beautiful is good.”—Sappho, the Greek lyric poet (630 B.C.).

It is a platitude to discuss beauty in social science. The history of humans pursuing beauty can be traced back to the era before Christ. However, in the area of economics, the new arrival of a “beauty economics” is inspiring and exciting. Hamermesh and Biddle published a seminal article in 1994 which focused on the correlation between physical attractiveness and labour market outcomes. Since then, this new field has come into prominence and economists have been encouraged to explore the role of appearance in determining labour income.

In the literature in this area, three alternative measures of physical attractiveness are commonly used: (1) Attractiveness as rated by the interviewers at the start or the end of the interview (Hamermesh and Biddle, 1994; Pfeifer, 2012), (2) attractiveness based on facial photographs of profiles or resumes rated by researchers or employers (Pfann, Biddle, Hamermesh, and Bosman, 2000; Mobius and Rosenblat, 2006), and (3) self-reported attractiveness (French, 2002; Pfeifer, 2012). In contrast to the self-rating system, the first two measures depend on others’ perceptions of an individual’s attractiveness.

Due to the fact that preferences are influenced by race, gender, age and region, bias in measures of attractiveness is inevitable (Hatfield and Rapson, 2000). Furthermore, the judgement standards may change over time. (Hamermesh and Biddle, 1994). For example, in China, females admire slender figures, while during the Tang Dynasty of ancient China and in Western countries today, people value a full-figured body most. For objectivity, the evaluations of a bystander are favourable when studying discrimination in the labour market.

Moreover, in their book, Hatfield and Sprecher (1978) demonstrate that physical attractiveness can be measured with photographs. This method is approved by many researchers. But I disagree with them because the photographs can now be retouched after processing with programs such as Photoshop. The distorted photos cannot possibly represent the real level of an individual's attractiveness and this makes the results biased.

Hamermesh and Biddle (1994) demonstrate the advantage of rating attractiveness using photographs. However, Biddle and Hamermesh (1998, 178) show that a photograph cannot capture facial features perfectly. As a result, all the attractiveness measuring approaches are feasible in research. Since I am restricted by my data set, attractiveness as rated by the interviewers at the start and at the end of interviews will be used in my paper.

The effect of physical attractiveness on earnings may be related to the "taste for discrimination", which was first introduced by Gary Stanley Becker (1971). Becker-type discrimination is an employer's personal prejudice depending on their preferences. In the first study of discrimination caused by attractiveness in the labour market, Hamermesh and Biddle (1994) state that pure employer discrimination exists because the effect of an individual's appearance is independent of occupation. The theory of Becker-type discrimination is used by Mobius and Rosenblat (2006) to analyze beauty discrimination. In their paper, employer discrimination is defined as Becker-type, while other types of discriminations are defined as non-Becker type. In addition, these economists use the term "beauty premium" to refer to the fact that more attractive people earn more. In contrast, they use "beauty penalty" to define the decrease in earnings caused by physical attractiveness.

My paper aims at providing further evidence on the empirical models estimated by

Pfeifer (2012), which examine the relationship between physical attractiveness, employment and earnings, and the theoretical models referred to by Fletcher (2009), Yankow and Horney (2013), and Bhatti et al. (2011). The main purpose of my paper is to examine whether the conclusions of Pfeifer (2012) hold or not. Pfeifer (2012) focuses primarily on attractiveness and does not show the estimation results for other important explanatory variables. Also, I try to explain the regressions in more detail than does Pfeifer (2012).

In addition to data selection, there are three other differences between this paper and Pfeifer (2012). First, I did not use self-reported attractiveness or estimate simultaneous quintile regressions. Second, the explanatory variables are different. Placing more attention on human capital than did Pfeifer (2012), I redefine the education variables. Body Mass Index, marital status and religion are also taken into account in my models. Third, the magnitudes and the significance of estimated coefficients are slightly different from those of Pfeifer (2012) due to the differences in sample selection and model specification.

This paper is organized as follows. Section 2 reviews the literature on the relevant topic and theoretical models. In section 3, the two econometric models used to analyze the relationships among physical attractiveness, education, employment and earnings are described. In section 4, the data and sample selection are discussed. The empirical results are analyzed in section 5 and the conclusions are compared with those of Pfeifer (2012) in section 6.

2. Literature Review

The references in this paper can be categorized into two types of literature related to the labour market. Most of the existing literature I refer to addresses the effect of physical attractiveness on earnings and employment status. In particular, a substantial literature on the effect of physical attractiveness on earnings and employment possibilities supports the view that good-looking people have an advantage in the labour market. I also refer to a few econometric articles on human capital that show that there are interactions between earnings (employment) and abilities (intelligence or education).

Daniel S. Hamermesh is one of the pioneers who first explored the relationships between earnings and physical attractiveness. He wrote a series of papers on beauty with a variety of co-authors, and many important results in this field come from his articles. For example, the seminal article written by Hamermesh and Biddle (1994) is considered to be the cornerstone of this domain. Their affirmations are widely accepted by other economists like Mobius, Rosenblat and Pfeifer.

In their article, Hamermesh and Biddle (1994) state that there are three possible reasons why individual appearance has a significant impact on wages : employer discrimination, customer discrimination and occupational crowding. Using the interviewers' ratings of the interviewees' physical appearances and a human capital earnings model, they find that earnings and physical attractiveness are positively correlated and assert that due to a preference for beauty, the prettier individual earns more. Furthermore, they estimate that the earnings penalty for unattractiveness is five to ten percent more serious than the beauty premium.

Hamermesh and Biddle suggest that it is necessary to estimate the effects for males and females separately and they successfully show that for males, the effects of attractiveness are not smaller than for females. In addition, the probability of employment is lower than average for unattractive women and married men. They also conclude that to some extent, beauty can enhance productivity, and that pure employer discrimination exists because of the independence between occupation and appearance.

Hamermesh and Biddle (1994) use three data sets to obtain these results: the 1977 U.S. Quality of Employment Survey, the 1981 Quality of American Life Survey and the 1981 Canadian Quality of Life Study. Occupation is a principal explanatory variable in their wage model; however, in the ALLBUS 2008 data set (Terwey, 2000) that I plan to use, the occupation is known only for those who are employed. It cannot be included in models of employment status, because occupation predicts employment perfectly so that its marginal effect is not estimable. Thus, the models estimated in this paper do not include occupation. I think this is also a potential reason why occupation is not taken into account in Pfeifer (2012).

The biggest limitation of Hamermesh and Biddle (1994) is that the data sets used are too old. Therefore they cannot efficiently reflect beauty standards in modern society. The effects of factors such as beauty on labour market outcomes need to be updated.

In addition to household survey data, Biddle and Hamermesh also use data for specific occupational groups. For instance, in Biddle and Hamermesh (1998), they conduct a study of the relationship between physical attractiveness, productivity and discrimination on the one hand, and the earnings of lawyers on the other hand. They conclude that the wage gap is usually used as a measure of discrimination in the labour market. This implies that it is necessary and indispensable to estimate a wage model in my study. Their paper provides further evidence in favor of the notion that "attractiveness is an advantage" (as pointed out by novelist P.D James in her 1995 novel *Original Sin*). Measuring the attractiveness of individuals through their photographs, they successfully show that the clients' taste for discrimination raises the labour income of better-looking lawyers in a particular law school. However, their survey data is once again very old, ranging from 1969 to 1984.

Inconsistent with their previous standpoint in 1994 that attractiveness can be reliably measured through photographs, Biddle and Hamermesh (1998) show the drawbacks of rating attractiveness using photographs. They also pay attention to different tastes for beauty depending on the demographic characteristics of the raters. We can learn from their creative approach to measuring attractiveness, which consists of using the average and standardized values of four different observers: a male under 35, a female under 35, a male 35 or older, and a female 35 or older. Hence, there are four observations of attractiveness for each individual. In addition, a five-scale system in which 5 represents most attractive and 1 represents most unattractive is used.

Another paper involving Hamermesh suggests that besides the individual's earnings, an employee's appearance affects the firm's revenues as well. Turning their attention to beauty capital, Pfann, Biddle, Hamermesh and Bosman (2000) examine relationships between executives' appearance and the profits of their companies using the data set of a Dutch advertising company. The attractiveness of employees is rated by photographs on their personal profiles and the profit maximization model includes profits, firm size, beauty capital and physical capital. They draw the conclusion that an executive with a better appearance will bring his or her company higher profits, and in return, the individual is more likely to get higher earnings. This provides powerful evidence that human capital (in the form of physical attractiveness) is able to explain why executive beauty is positively correlated with company's profits.

This result is shown to be reasonable in the competitive labour market, which raises the question of whether there would be opposite conclusions in other labour markets. In different types of firms, such as private enterprises and share-holding enterprises, will the conclusions of Pfann, Biddle, Hamermesh and Bosman (2000) still hold, and what will the difference be? These are interesting questions we need to study in the future.

Hamermesh, Meng and Zhang (2002) extended their exploration of the interactions between earnings and physical attractiveness using China's household survey data for 1988. Their results support the view that "beauty can enhance productivity," and reveal some interesting relationships: physical attractiveness is increased by beauty expenses, or spending on beauty-enhancing goods and services (Hamermesh, Meng and Zhang, 2002, 361), and earnings will be raised by physical attractiveness. In addition, beauty expenses are positively correlated with earnings. Nevertheless, the role of spending on beauty is overstated. The estimations show that the effects of attractiveness are not as large as people expect. In this paper, physical attractiveness is rated using a five-level scale which is different from the eleven-point ranking system in ALLBUS 2008.

Another innovation in this paper is that the Body Mass Index is used as a proxy variable for health status. The writers emphasize that although the impact of beauty expenses is overstated, the positive relationships indeed exist. Moreover, the sample is very restricted. For example, the authors only chose female individuals from the ages of 22 to 60. This is an efficient approach to avoid heteroskedasticity, but the number of observations is 853, which only accounts for about 28 percent of the whole sample. Additionally, Hamermesh et al. (2002) only take the spending on the wife's clothing and cosmetics into account. This does not conform to the growing trend of male cosmetics. Hence, we don't know whether the conclusions hold for males as well, or for females in other age groups.

In another article, Hamermesh (2006) discusses the role of looks and discrimination in elections. He suggests that beauty can also increase the probability of success in an election. One of the findings in this paper is remarkably different from those of the previous studies. Reducing the sample size has a negative impact on the significance of the estimated coefficient of beauty, but it keeps the estimate of "perceptions of beauty" stable. He demonstrates that in addition to physical attractiveness, other factors will affect the outcome in the labour market but these factors can not directly raise productivity. The data set relates to the election of officers of the American Economic Association. In total, there are 312 observations but only 216 different individuals, which means that the data may overlap. However, Hamermesh insists that the information can still be used because many candidates updated their photos in every election. I think that we cannot ignore the rater's past impressions of these candidates. Past impressions which affect the ratings may not easily change. For example, perhaps a candidate was known to have some skin problems, such as wrinkles. After micro plastic surgery, these problems have been solved but the raters possibly remember that these problems existed. Hence, this candidate cannot get as high a rating as expected. As a result, the data set is not ideal.

To provide further evidence of the positive relationships between beauty and labour income, French (2002) reviews wage differentials with respect to an individual's age, race and gender. His baseline model includes personal factors which have effects on wages (*X*) and four indicators representing worksites (*S*), the survey year (*Y*), unattractiveness (*U*) and attractiveness (*A*), respectively. The variable *U* indicates whether attractiveness is below average, and *A* indicates whether attractiveness is above average. Both variables are included in French (2002) rather than the level of attractiveness.

In contrast to most studies related to attractiveness, the variable he uses is the self-rated attractiveness of employees in two companies. The sample selection is random from 1995, 1996 and 1997 and the restrictions are the same as in Hamermesh and Biddle (1994). On the one hand, this is a new direction for research in this area. On the other hand, this innovation possibly causes biases in the results. Because of personal preferences regarding physical attractiveness, the self-rating system cannot represent the tastes of the employers. French successfully shows that earnings differentials exist with relatively recent data sets, but did not examine the beauty premium and plainness penalties.

Mobius and Rosenblat (2006) also follow up on Hamermesh and Biddle (1994), and in their paper they try to answer the question "Why beauty matters." This article attributes the beauty premium to employers' prejudices, which is slightly different from other studies that center on the interaction between customers and workers. They agree that an attractive-looking employee is more confident and better at communicating, and that this is an advantage that enhances the individual's labour income. Additionally, they find there is a large gap between men and women in the ability to solve mazes: in 15 minutes, men can solve 10.9 mazes on average, while women solve 7.8 mazes on average. However, they suggest that in contrast to popular belief, the relationship between a person's ability and physical attractiveness is often overestimated. The results show that the attractive individual is not more capable of working than the unattractive individual.

In their 1994 paper, Hamermesh and Biddle proposed that interpersonal interactions between employers and workers had an insignificant effect on the beauty premium. This proposition made Mobius and Rosenblat (2006) interested in studying the wage negotiation process between employers and workers instead of studying job performance related to the interactions between workers and consumers. In order to control for the pattern of interaction, they estimate an empirical model with decompositions of the beauty premium into "stereotypes" and "confidence" (Mobius and Rosenblat, 2006). Their basic model regresses the earnings of employees on four common factors, which are the employer fixed effect ( ), the employee's physical attractiveness ( ), and a dummy variable (*SETWAE*) that is an indicator showing whether the decider of employment is the employer or not, and a vector of characteristics of the employee's personality ( ). The dependent variable is earnings. The model is as follows:

, (2.1)

where represents *SETWAGE*, and the interaction term ( ) represent Becker's discrimination. is the error term.

Their data are generated by an experiment that is designed to show the effects of confidence, persuasive skills and stereotypes on earnings. Mobius and Rosenblat (2006) ask one group of participants, called workers, to solve computer mazes within 15 minutes as a test of confidence and ability. The other group of participants, called employers, are asked to evaluate the worker's performance and decide how much to pay workers. This paper shows that individuals with more attractive appearance do not have better performances than those with average attractiveness, but good-looking individuals seem to have more confidence than others. In addition, inconsistent with their expectations, physical attractiveness has no effect on earnings if employers rate workers' attractiveness through resumes. However, beautiful people are more productive through other channels in which there are personal interactions between employers and employees.

This perspective reminds future researchers to use caution when drawing a conclusion about interaction terms. Furthermore, aiming at decreasing the beauty premium from their results, they advise employers to avoid personal interactions. However, I think the decomposition of the beauty premium in Mobius and Rosenblat (2006) is not comprehensive. There are more potential components which are worth exploring. For instance, the beauty premium can be also decomposed into backgrounds, education levels etc. Hence, the models of future study will include the explanatory variables corresponding to these potential decompositions.

In his study of high school graduates, Fletcher (2009) also agrees that those who earn higher wages are often better-looking individuals rather than plain-looking individuals. He assumes that the earnings of workers are a function of a vector of individual and family characteristics (*X*), looks and ability. Fletcher's basic empirical model is simpler than French's:

, (2.2)

where *wage* is yearly reported earnings from employment divided by average weekly hours multiplied by 50 weeks. *Looks* is the individual's level of attractiveness and *Ability* is the PVT test score.[1]   is an error term. The data set is a national longitudinal study of adolescent health in the U.S., in which there are 4000 observations. The estimation results show that the marginal effects of attractiveness are correlated with an individual's ability. Hence, the interactions between the measures of physical appearance and ability cannot be ignored. Following the method of Hamermesh, Fletcher tries to estimate empirical models of earnings for different gender groups and was successful.

Two of Fletcher's conclusions are very notable. He finds that the test score measure is positively correlated with earnings, and that the very pretty and capable individual has a higher labour income. More importantly, for individuals at the same unattractiveness level, the one with higher abilities earns less than the one with lower abilities. Fletcher (2009) does not offer an explanation for this result. Another factor Fletcher takes into account is parental education level, which should be included in my study. However, ALLBUS 2008 does not include the relevant data.

Pfeifer (2012) uses data from a German survey called ALLBUS 2008, the same data set I use, to show the relationships between physical appearance, employment status and earnings. He uses three detailed measures of physical attractiveness, each of which uses an eleven-point scale: the attractiveness as rated by the interviewers at the start of the interview, the attractiveness as rated by the interviewers at the end and the attractiveness as rated by the individuals personally. Therefore, there are three specifications of the regression model, one for each attractiveness variable.

He agrees with three findings of previous studies and gives a brief introduction. Firstly,

1 Fletcher (2009) uses the PVT test score as a proxy for   .   PVT is an acronym for the Peabody Picture Vocabulary Test.

he suggests that there may be a positive relationship between physical attractiveness, non-cognitive or social skills and sympathy feelings, which means that if we increase the physical attractiveness of employees, they are more likely to be able to work more efficiently. He shows algebraically that the derivative of the marginal productivity of labour with respect to physical attractiveness is definitely positive. Additionally, the derivative of earnings with respect to physical attractiveness is also considered to be definitely positive, because he insists that the employment probability and labour income of an attractive individual is higher than that of an unattractive individual. This is one of the reasons why employers are more likely to hire someone with outstanding looks.

The second reason why employers are more likely to hire attractive individuals is that it is difficult for an unattractive employee to promote sales because of the theory of the beauty premium. The physical attractiveness of a salesman or saleswoman can increase the consumers' interest and willingness to purchase. To pursue high profits, it is a smart decision for employers to choose good-looking employees and it is worth offering them higher salaries than the average-looking employee. Consistent with Hamermesh and Biddle (1994), Pfeifer also asserts that a "taste for discrimination" exists not only for consumers, but also for employers. Employers, therefore, appear more generous by offering the beautiful individuals a position and higher wages.

Starting with these three major premises, Pfeifer uses the German data set, ALLBUS (2008) and finds that:

(1) The better-looking individual is more likely to get a job than the plain-looking individual and he or she earns more with a higher probability of being hired.

(2) The marginal effect of attractiveness rated by the interviewer is more substantial for men than for a woman, as was found by Mobius and Rosenblat (2006).

(3) The perception and the evaluation of the interviewer are more important than the individual's cognizance of self-attractiveness.

(4) The marginal effect of attractiveness is non-linear for men. In contrast, there is a linear effect for women. Additionally, it is always positive at each wage level.

Pfeifer's study provides a strong foundation for the econometric analysis of topics related to physical attractiveness and earnings. His methodology is inspiring. He uses the binary probit model to examine employment possibilities, and estimates labour income effects through Ordinary Linear Squares estimation of both a linear and a quadratic model of the relationship between attractiveness and earnings.

However, his investigation is too simple because there are limitations to his models. Pfeifer does not explain his models and analyses in detail. He does not explain his selection of variables either. Moreover, there are five different marital statuses in ALLBUS 2008, but Pfeifer does not provide the statistical information about which marital status category his variable represents.

In addition to the papers already discussed, four other studies guided me in specifying my own models. Dooley (1986) provides a useful example of human capital wage functions in his analysis of the over-education of Canadian men during the period from 1971 to 1981. In this paper, he employs a log-level model to demonstrate the relationship between earnings, education and a quadratic function of age. Due to the limitations of his longitudinal data set, Dooley (1986) uses age as a proxy for experience. The dependent variable is the mean of the natural logarithm of yearly (or weekly) labour income ( ). The control variables are age ( ), the square of age ( ), the unemployment rate ( ), the logarithm of the number of observations in cohort *it* ( ), time (t), and the percentage of age group *i* that usually worked part-time ( ). His estimating equation is thus:

, (2.3)

where is error term.

Considering the difference between years, a first difference model is applied and the results show that labour income is diminishing with age and that at different education levels, earnings vary. This result is also obtained in my work using a different approach.

Another helpful reference is Fleming and Kler (2008), who estimate a bivariate probit model exploring over-education and worksite satisfaction. For men in Australia, the bivariate probit model turns out to be better than to estimate two binary probit models separately. Because there are interaction effects among the factors which cannot easily be observed, ignorance of the overlap will bias the estimates due to endogeneity. This specification of the model is more complicated than the probit model applied in my paper. This paper is an important reference to set up my binary probit models.

After reviewing these articles about binary probit models of employment status and labour force participation, I decided upon my employment status model. The experimental research of Yankow and Horney (2013) emphasizes the importance of marital status and the number of offspring when estimating models of job search behaviour in young women. Their paper includes a binary probit model with some independent variables in quadratic form, such as *age* squared/10 and *tenure* squared/10. This is also an important paper for me to set up probit models. Moreover, I expect a negative effect of marital status because Yankow and Horney (2013) show that being married has a negative effect on employment. Another useful study of a binary outcome model of employment is that of Bhatti et al. (2011). In this model, labour income and the expense of raising children are deemed to affect the likelihood of employment for females. The only problem with those econometric models is that they do not include physical attractiveness.

In the previous studies, several important questions remain unanswered. For example, researchers did not show how seriously the physical attractiveness can affect the level of earnings. Moreover, besides physical attractiveness, are there other personal characteristics which have effects on earnings, such as education, health status, and marital status. The previous studies just took one or two of these three factors into consideration and did not clearly explain why.

For further study in this area, it is important to add two variables into the models: Body Mass Index and religion. Body Mass Index is included in both the employment model and the earnings model in my paper. In addition, there are five religion variables in the employment model. It is important to note that the marital status variables are defined differently in each sample. The creativities in this paper are the calculation of marginal effects at two representative values of attractiveness, most unattractive and most attractive, in the probit models, and the calculation of turning points of physical attractiveness for the Ordinary Least Squares regression models, which will be discussed in the next sections.

3. The Empirical Model

In this section, I describe two econometric models to analyze the relationships among attractiveness, education, and labour market outcomes. For employment, with a dummy variable reflecting the current employment status as the dependent variable, a binary probit model is used. For earnings, the method of ordinary least squares is applied to a human capital wage equation with the natural log of annual net labor income as the dependent variable. All models are estimated separately for men and women as well as for the pooled sample.

3.1 Employment

For binary outcome data the dependent variable *y* takes one of two values indicating whether the individual is employed or unemployed. Without loss of generality, the values are set to 1 if employed and 0 if unemployed. The probability of the employed state is given by *p*.

For my econometric analysis, I employ a binary probit model similar to those of Bhatti et al. (2011) and Yankow and Horney (2013) in order to explore the employment effects examined by Pfeifer (2012). The model is given as follows:

, (3.1)

where is the probability of employment, the dependent variable ( ) is the employment status variable, and *i* represents the individual. is the cumulative distribution function of the standard normal distribution as follows:

, (3.2)

where represents the physical attractiveness rating. is a vector of other factors affecting employment status.

After estimating the probit models, I compare average marginal effects instead of marginal effects at the means. One of the reasons why the non-integer average value of a variable may not make sense, for example, is that although 32.65 years old is not meaningless, we usually would say “thirty-two years old” or “thirty-three years old.” Another reason is that as Williams (2011, 32) points out "the means are only one of many possible sets of values that could be used – and a set of values that no real person could actually have seems troublesome." To show how the marginal effects vary across the different levels of attractiveness, this paper gives a direct illustration of the beauty trade off by computing some key marginal effects for the attractiveness values of one and eleven.

3. 2 Earnings

My sample is different from Pfeifer's (2012) due to my selection of variables, and my starting point with respect to earnings is to test whether Pfeifer's (2012) conclusions hold for my sample as well. The initial specification of the OLS model is simple. Using the earnings sample, I try to uncover a relationship between earnings, attractiveness and education. Following equation (2.2) proposed by Fletcher (2009), the log of earnings of the employed workers is assumed to be a function of a vector of personal characteristics, looks and ability. Considering the workers' physical attractiveness, sex, education levels, ages and the regions where the interviews were held, health status and marital status, the simple OLS model is modified as follows:

, (3.3)

where X is the vector of personal characteristics and *Education* is a vector of education variables.

In the earnings model, I expected interaction effects between the physical attractiveness ratings and the education levels. However, the preliminary estimations, which are not concluded in this paper, show that the interaction terms are a weighted function of education levels leading to a severe multicollinearity problem. As a result the estimates of the education coefficients differ greatly from those of the basic models while the other coefficients are almost unchanged. Therefore, I did not use the models with interaction terms.

To further study the relationship between labour income and attractiveness, as Pfeifer (2012) does in his paper, I re-estimate the original simple Ordinary Least Squares models with the additional squared term of the attractiveness rating added to the model. These quadratic functions are used to capture decreasing or increasing marginal effects of attractiveness.

4. Data and Sample Selection

In the following subsections, the data set used in this paper is introduced and the sample selection is explained. The data set is ALLBUS 2008, which is used by Pfeifer (2012). However, the sample selected is different from that of Pfeifer (2012). Table A1 lists all the variables in ALLBUS 2008 that are used in this paper. Table A2 presents the dependent variables and the explanatory variables in the employment and earnings samples.

4.1 Sample Characteristics

ALLBUS 2008 is a German General Social Survey collected by GESIS.[2] The survey includes 3,469 individuals from both East Germany and West Germany who were asked

[2] GESIS, the Leibniz-Institute for the Social Sciences, is the largest infrastructure institution for the Social Sciences in Germany.

about attitudes, behaviour, employment, income, education, attractiveness and social structures, etc., in Germany in 2008.

As in Pfeifer's study, the data are confined to two main sample groups in my paper: the employment sample, and the earnings sample. The differences between the two samples reflect the serious theoretical and econometric problems differences in the analysis of employment status and earnings of the individuals in the interviews. Both samples are subject to some conditions. For earnings, they include all individuals for whom yearly net labour income is reported. Hamermesh et al. (2002) also proposed choosing an age-group from 22 years old to 60 years old. However, today, more and more seniors choose to pursue their careers. Following this trend, I will not impose an age restriction for sample universality. The age of the respondents is from 18 to 97. In addition, Hamermesh et al. (2002) choose all those who work at least 30 hours per week. Considering that 55 percent of the total population worked less than 30 hours in ALLBUS 2008, I do not set an hours of work restriction on the samples.

In the employment sample, there are 2,764 observations with useful information. In contrast to Dooley (1986), I do not take the reasons why the individual is out of labour force into account and self-employed and family workers are not omitted from the sample. Since Pfeifer (2012) does not provide information about the sample size used to estimate his employment model, I cannot compare my sample with his. The earnings sample is more restricted because the unemployed individuals were excluded; this restriction reduces sample size by nearly 50 per cent and the number of observations is 1,422. In comparison to the earnings sample in Pfeifer (2012), which is 1224, my sample size is bigger. There are 692 men and 532 women in his sample, as compared to 864 men and 618 women in mine.

4.2 Definition of Dependent Variables

There are two dependent variables in my paper. One is for the models of the employment effect and the other is for the models of the wage effects. In the employment model, the dependent variable is the employment status indicator. It is renamed *employment* in the data set. Specifically, it indicates the individual’s employment status, where being employed leads to $y = 1$ and not being employed leads to $y = 0$.

Besides the variables related to the physical attractiveness, eleven variables are measured to influence the binary employment outcome variable. Considering the information from demographic investigation, education, age, sex, region where the interviews were held, health status, marital status, occupation and even religion are taken into account. The main purpose of these explanatory variables is to capture their effects on the employment status.

In the earnings model, the dependent variable is named *lwage*, which represents the logarithm of the yearly net labor income. Some economists suggest using a weekly net income, which is the weighted average of the annual income. For example, Fletcher (2009) assumes that employees work for 50 weeks a year, so the weekly net income should be

(4.1)

where y is the weekly net income, x is the yearly net income, and 50 represents the assumption of 50 weeks per year. However, Pfeifer (2012) tends to use the monthly net income instead.

In my case, I take the logarithm of the yearly net income directly because we have no information about how many weeks the individuals worked in our samples. Since all the individuals in this earning sample are employed, I assume that the annual net income is the wage (earnings) of the employee, or the labour income.

4.3 Definition of Explanatory Variables

In the employment model, I include nineteen explanatory variables reflecting human capital and individual characteristics. In addition, there are two attractiveness variables measuring the physical attractiveness of the interviewees. The goal of the physical attractiveness variables is to capture the effects of the individual's appearance. During the interview, each individual's appearance was rated twice, once by the interviewer at the start and again by the interviewer at the end. The attractiveness variables are covariates measured using an eleven-point ranking system, with 1 indicating the most unattractive and 11 indicating most unattractive. Hence, I have two attractiveness variables:

(1) *attstart*: the attractiveness as rated by the interviewer at the start

(2) *attend*: the attractiveness as rated by the interviewer at the end.

There is no perfect collinearity between *attstart* and *attend*. However, these two variables are highly correlated because calculations show that the coefficient of correlation between them is 0.8466. I expect a positive sign for the coefficients of these physical attractiveness variables, because the more attractive the individual, the more likely he or she will be employed and the higher the wage he or she will get. Hamermesh and Biddle (1994, 1174) said "Plain people earn less than average-looking people, who earn less than the good-looking." In the earning model, there are two additional attractiveness variables:

(3) *attstartsq*: the squared value of attstart, the attractiveness as rated by the interviewers

at the start

(4) *attendsq*: the squared values of attend, the attractiveness as rated by the interviewers at the end.

The education variables of the models measure the education level of individuals and are meant to capture the impact of education on employment status. All are expected to have positive coefficients. They are constructed from three variables chosen from the data set: general school leaving certificate, university of applied sciences degree and university degree. There are three principal general school leaving certificates - the Certificate of qualifying for studies at a University of Applied Sciences, the Certificate of qualifying at the university level and other school leaving certificate. If the individual has one of these three types of certificates, I consider them to be at a high educational level. More precisely, I define the variable, *heduc* as follows:

(5) *heduc*: a dummy variable for general school leaving certificate

Other educational variables from ALLBUS 2008 indicate the highest level of education actually obtained. I used these variables to conduct two additional educational variables as follows:

(6) *usadegree*: a dummy variable for university of applied sciences degree

(7) *udegree*: a dummy variable for university degree

Because graduating with a high level of education is a prerequisite for attending either type of university, *heduc* will be equal to 1 if *usadegree* =1 and/or *udegree*=1. In addition, there are some individuals who are qualified to enter university but do not do so.

Work experience is very important to the study of employment in the labour market because experienced workers are usually more sophisticated and skilled than new entrants. This is a crucial advantage for them when hunting for a job. Employers prefer to hire an experienced worker because they can save on the costs of training their employees and at the same time, the risks of job-hopping are avoided to some extent. However, as in the Survey of Consumer Finances data sets used by Dooley (1986), ALLBUS 2008 does not include the information needed to provide a good measure of experience. Therefore, I use the age of the interviewee and its square instead of experience. Work experience usually has a positive impact on earnings. However, the expected sign of the coefficient of *age* is positive and that of *agesq* is negative. Another problem with using age as a proxy is that it is likely to be less accurate for women as they are more likely to have spent time out of the labour force to raise children.

Some human capital studies assert that the probability of employment first increases and then decreases with age. The older workers are, the more sophisticated they are, and employers are more likely to hire sophisticated workers. But after some age level, the situation is reversed. For example, Göbel and Zwick (2009, 4) argue that the relationship between age and performance matters: "If [an] aging workforce leads to a decrease of productivity then this is likely to lead to welfare loss." As a result, *age* is expected to have a significant negative effect on employment status. As in Pfeifer (2012), the two variables created are

(8) *age*: the age of the interviewee in years.

(9) *agesq*: the squared value of *age*/100.

A number of other variables are also included in the models. The first is a dummy variable, *female*, that represents the gender of the individuals. If the individual is female, I record the value as one. Otherwise, it is zero.

(10) *female:* a dummy variable for sex of the interviewee

I expect the coefficient of this variable to have negative effects, because previous studies show that women usually have lower wages and employment than men on average.

For the region of the interview, I use another dummy variable, *EGermany*:

(11) *EGermany:* a dummy variable for region of the interview.

I do not have any expectations about the signs. In order to distinguish the pure physical appearance from the physical health status, we use a Body Mass Index to be the proxy of health status.

(12) $\frac{\quad}{\quad}$,

where the unit of the weight is kilograms and the unit of height is meters. I think Body Mass Index can also reflect physical attractiveness to some extent. One of the reasons is that, if an individual is obese, he or she is also less attractive in the modern world.

I also take the marital status of the interviewee into account because Yankow and Horney (2013) argue that both marriage and children significantly reduce the likelihood of on-the-job search for young women. In the earnings model, marital status is represented by an indicator variable which is called "*mastatus*" and is expected to have a negative effect on earnings. Pfeifer (2012) does not give a definition of his or her marital status variable; I define a dummy variable for marital status in the earnings sample as follows:

In the employment sample, I include four marital status variables: married but living apart, widowed, divorced, and never married. The reference category is being married and cohabiting.

The religious denomination of the interviewee is also included, but it is only used in the employment status model. In all, five religion variables are defined:

To avoid collinearity, the sixth religious denomination, called "non-affiliation", is omitted; it accounts for 35.49 percent of the total observations.

In addition, it is common in labour market research to take into account the current occupation. However, in the probit model, occupation predicts success perfectly so that the marginal effect is not estimable.[3] As a result, my model does not include variable for occupation.

To summarize, the probit models of employment status include an attractiveness variable (attstart and attend), *heduc*, *uasdegree*, *udegree*, *age*, *agesq*, *female*, *EGermany*, *BMI*, four marital status variables, and five religion variables. The simple earnings models include an attractiveness variable, *heduc*, *uasdegree*, *udegree*, *age*, *agesq*, *female*, *EGermany*, *BMI*, and

[3] The current occupations included in ALLBUS 2008 are independent farmer, independent professional, self-employed, civilized service and soldiers, employee, worker, in vacation training, and helping family member. The occupation is provided only for those who are employed.

mastatus. Finally, the second set of earnings models adds the square of the attractiveness variables to the list.

4.4 Descriptive Statistics

Table 1 provides sample mean values for the employment sample. Using the different values of the dummy variable *female*, I specify three samples: the full sample, males and females. There are 1416 men and 1348 women in the full sample. Table 2 provides mean values for the earnings sample in which the individuals are employed workers. There are 804 men and 618 women in the full sample.

With respect to employment status, males have the largest mean at 0.5946, while females have the lowest mean of 0.5378. We can infer from these statistics that, on average men are more likely to be employed than women. For comparisons, I regard the full sample as the reference point. The sample mean of *heduc* is a little higher than average for men with a value of 0.3121 and lower than average for women with a value of 0.2552. The sample mean of *uasdegree* is much higher than average for men with a value of 0.0833 and lower than average for women with a value of 0.0408. The sample mean of *udegree* is also higher than average for men with a value of 0.1434 and lower than average for women with a value of 0.1091. Thus the sample proportion of individuals with high levels of education is greater for men than for women.

In terms of the attractiveness rated by the interviewer at the beginning and the end, which ranges from 1 to 11, in the employment sample the means for females are the highest with values of 7.4964 and 7.6039, while the means for males are the lowest with values of 7.2415 and 7.3588. This means that generally female individuals receive a better rating from the interviewers than male individuals, and that the interviewers' impressions of the female individuals are more dispersed.

For the full sample, the attractiveness as rated by the interviewers at the beginning of the interviews is slightly smaller than the attractiveness as rated by the interviewers at the end. This implies that the individuals seem more attractive after communicating with the interviewers during the interview for reasons such as personnel competence and non-cognitive skills.

As for earnings, males have the largest mean of the natural logarithm of net labour income at 7.4111, while females have the lowest mean of 7.0196. We can infer from the statistics that, on average men get higher wages than women in labour markets and that the dispersion of wages in the male subsample is more serious than in the female subsample. The descriptive statistics for the explanatory variables in the earnings sample are almost identical to those of Pfeifer (2012), except for the educational variables and the marital status variables because of the definitions of these variables are different from those of Pfeifer (2012). For *heduc* and *udgree* the average values are identical. In contrast, the mean values of *usadegree* are a little higher for men than the overall average with a mean value of 0.0871, and they are lower for women than the average with a mean value of 0.0599.

In terms of the attractiveness rated by the interviewer at the beginning and the end, which ranges from 1 to 11, the means for females are the highest with values of 8.0663 and 8.1456, while the means for males are the lowest with values of 7.6965 and 7.7985. For the full sample, the attractiveness as rated by the interviewers at the beginning of the interviews is also slightly smaller than the attractiveness as rated by the interviewers at the end. What I find regarding the beauty variables in my sample is consistent with Pfeifer (2012).

5. The Empirical Analysis

Table 3 reports the results for the probit model of employment (in the form of marginal effects) and Table 4 reports the marginal effects of the selected variables for the most attractive and most unattractive individuals. In section 5.1, I explain the probit results in detail. Table 5 presents the estimates of regressions of log wages on a linear function of attractiveness, while Table 6 presents the results of regressions of log wages on a nonlinear function of attractiveness. These results for the earnings sample will be discussed in sections 5.2 and 5.3.

To extend the study of this topic, I planned to modify the regression by adding interaction terms between physical attractiveness and education levels, but found that their coefficients were not estimable with my sample due to multicollinearity. Hence I had to give up this regression.

5.1 Employment Effects

Table 3 reports estimation results for two alternative specifications of the binary probit model of employment status, which differ in terms of the choice of the physical attractiveness variable. Marginal effects, not coefficient estimates, appear in table 3.[4] Consistent with Pfeifer (2012), the statistical significance and the signs of the coefficients are almost identical for the two specifications, so for discussion purposes, I use specification (1) as a starting point. The pseudo R-squared value is relatively stable across equations and it rises from 0.1607 in Pfeifer (2012) to 0.430 as variables are added to the model. Using the Likelihood Ratio Chi-Square test, we can reject the hypothesis that all the slope coefficients in the probit model are simultaneously zero at common significance levels. The predicted probability of employment is almost identical for the two specifications; for instance, the predicted probability for the full sample is 0.5676 in specification (1) and 0.5679 in specification (2). However, they do not seem to be statistically different from each other.

In specification (1), the absolute values of the marginal effects of the attractiveness variables are smaller than the marginal effects in specification (2). Before analyzing these marginal effects, I examine those of the other explanatory variables. As for the age variables, although both *age* and *agesq* are included in the model, only one marginal effect measuring their combined effect appears in Table 3. The marginal effects are negative and significant at the 1% significance level for all the samples, and highly stable across subsamples. Hence, I focus on the results for all individuals in specification (1), which includes attractiveness rated by the interviewer at the start. In this specification, the marginal effect of age for the full sample is -0.0115, and it is -0.0140 for men. The marginal effect of age is -0.0088 for women. These results are consistent with my expectations.

[4] For the probit model with attractiveness rated by the interviewers at the start of the interview (specification (1)), there are 12 failures and 0 successes completely determined. For the probit model with attractiveness rated by the interviewers at the end of the interview (specification (2)), there are 13 failures and 0 successes completely determined.

Turning now to gender, the marginal effect of being *female* is -0.0363 in specification (1) and -0.0376 in specification (2). They are both significant at the 1% significance level, which suggests that if you had two otherwise identical individuals, one a man and one a woman, the woman's probability of employment would be 3.6 to 3.8 percentage points lower. This indicates that women are less likely to be employed relative to men.

The marginal effect of region (*EGermany*) is almost identical in the two specifications. In specification (1), it is negative and significant at the 1% significance level for the full sample and for men. In particular, the marginal effect for the full sample is -0.0734. The marginal effect for the male sample is -0.113 and that for the female sample is -0.0328. The marginal effect indicates that when attractiveness is rated by the interviewer at the start (specification (1)), an individual who attended the interview in East Germany is about 7.3 percentage points less likely to be employed than one who attended the interview in West Germany. Concerning the attractiveness rated by the interviewers at the end (specification (2)), an individual who attended the interview in East Germany is 7.2 percentage points less likely to be employed than the one who attended the interview in West Germany.

The marginal effect of the Body Mass Index (*BMI*) is about 0.002 except in the case of men when attractiveness is rated by interviewers at the end (specification (2)). The estimated marginal effect is about 0.0003. None of the estimated marginal effects of the Body Mass Index are significant at common significance levels, which imply that the Body Mass Index has little effect on the employment status of individuals.

With respect to marital status, the negative sign of the marginal effects is in accordance with the expectation that not being in a stable relationship reduced the probability of employment. Among these statuses, married and cohabiting individuals are the reference. For married but living apart individuals, the marginal effects are similar for both specifications for the full sample and for women. For the full sample, it is -0.136 and for women it is -0.193. Both of them are statistically significant at the 1% significance level, which means that relative to the married and cohabiting individual, the probability of employment for married but living apart individuals is significantly lower by 13.6 percentage points for the full sample and 19.3 percentage points for women. In contrast, the marginal effect is -0.0375 or -0.0449 for men and it is not significant.

For widowed individuals, the magnitudes of the marginal effects are smaller and the marginal effects are insignificant for all samples. For divorced individuals, in specification (1), the marginal effect is -0.0642 and significant at the 1% significance level for the full sample, -0.0796 and significant at the 5% significance level for men and -0.0545 and significant at the 10% significance level for women. The marginal effects for the full sample in specification (2) are slightly smaller. For never-married individuals, in specification (1), the marginal effect is -0.0595 and significant at the 1% at for the full sample, -0.101 and significant at the 1% significance level for men and -0.0190 but insignificant for women. Thus, there is no significant difference between married and never married women.

The marginal effects are insignificant for most of the religion variables, except for the non-Christian-denomination individuals (*religion5*). The marginal effect of belonging to a non-Christian denomination (*religion5*) is almost identical in the two specifications. It is negative and significant at the 1% significance level for the full sample and for men. In particular, in specification (1), the marginal effect is -0.144 for the full sample, and the marginal effect is -0.226 for men. The marginal effect is 0.0479 for women, but it is not significant.

Turning our attention to the physical attractiveness variables, there are three main findings. First, the results are consistent with the expectation of a significant positive effect at the 1% significance level. Second, the marginal effect of attractiveness rated by interviewers at the start is smaller than the marginal effect of attractiveness rated by interviewers at the end. Third, the marginal effect of attractiveness for women is smaller than that of men. In particular, for all individuals, the marginal effect of attractiveness rated at the start is 0.0193, which implies that the individual's probability would be 1.9 percentage points higher if attractiveness was 1 unit higher. The marginal effect of attractiveness rated at the end for the full sample is 0.0226, which implies that if the individual received a rating that was one point higher, the probability of employment would be 2.3 percentage points higher. In conclusion, to some extent the attractiveness rated by the interviewers at the end appears to be more important for individuals than attractiveness rated at the start.

Surprisingly, the marginal effects of attractiveness are larger for men than for women, but the difference are very small. In particular, if a male individual receives a one-point-higher rating at the start of the interview, his probability of employment would be 2 percentage points higher. In comparison, if a female individual receives a one-point-higher rating at the start of the interview, her probability of employment would be 1.8 percentage points higher. This result also accords with Pfeifer (2012). However, this difference is not statistically significant.

In terms of educational variables, almost all the estimated coefficients of *heduc* are insignificant. However, the coefficient of a university of applied science degree (*uasdegree*) and university degree (*udegree*) are positive and significant. The marginal effects of these variables are larger in specification (1) than specification (2) for the full sample and for men, but the differences are small. In specification (1), for all individuals, the marginal effect of *uasdegree* for men is about 0.133. This indicates that a male individual with a university of applied sciences degree is 13 percent points more likely to be employed than a male individual without a degree and it is significant at 0.5% significance level. For women, the marginal effect of *uasdegree* is 0.034. Thus men with a university of applied sciences degree are 10 percent points more likely to be employed than women with the same degree. It is not significant for women.

Concerning *udegree,* for all individuals, the marginal effect is 0.148, which indicates that an individual with a university degree is 14.8 percentage points more likely to be employed than an individual without a university degree. A male individual with a university of applied sciences degree is 4 percentage points more likely to be employed relative to female individuals. In addition, the marginal effects are larger in specification (1) relative to specification (2), especially for men than women. But the difference is not large. However, the marginal effect of *udegree* is significant at 0.01% significance level for men while significant at 0.5% significance level for women.

To get some insight into how the marginal effect of a one-unit change in the eleven-point scale of attractiveness and education differs with the level of attractiveness, the marginal effects were re-calculated for the most unattractive individual (1 in the eleven-point ranking system) and the most attractive individual (11 in the eleven-point ranking system). In other words, the values of the attractiveness variables were fixed at these values for all individuals for the purposes of the new calculations; marginal effects were once again computed by averaging across individuals, given the value of attractiveness. These marginal effects can be found in Table 4.

The resulting marginal effects of attractiveness and education at the two levels of attractiveness are consistent with previous results. In addition, one can see that for all the subsamples, the marginal effects are larger for the least attractive (attractiveness = 1). Taking the estimations for full sample in specification (1) as an example, the marginal effect of attractiveness rated by interviewers at the start for full sample is 0.0226 at level 1. In contrast, the marginal effect of attractiveness rated by interviewers at the start is 0.0176 for those who are already at level 11.

I also find that for *heduc*, the marginal effects lack significance, which means that there is no significant difference between individuals with high education and individuals with low education. However, the degrees do matter. As far as a university of applied science degree (*uasdegree*) is concerned, at level 1, the marginal effect is about 11 percentage points. For the most attractive individuals, the marginal effect of a university of applied science degree is about 9 percentage points. Similarly, for an individual with a university degree (*udegree)*, the marginal effect is about 17 percentage points for the least attractive individuals and almost 14 percentage points for the most attractive individuals. This result suggests that a person with outstanding looks is less likely to be employed relative to an ugly person at the same education level with a university of applied science degree or a university degree. This also occurs in the male subsample and female subsamples.

5.2 Log Earnings as a Linear Function of Attractiveness

The parameter estimates for the earnings models in which attractiveness enters in a linear fashion are presented in Table 5. Table 5 presents the coefficient estimates and tests for overall significance, for normality of the errors and for heteroskedasticity.

For the full sample and for men, the Jarque-Bera test statistic is larger than the critical values of chi-2 at common significance levels. Hence, I can reject the null hypothesis of normality in the error distribution. Furthermore, with respect to heteroskedasticity, the Koenker version of the Breusch-Pagan-Godfrey test statistic and White's test are more persuasive than theBreusch-Pagan-Godfrey test statistic due to the fact that the errors are not normally distributed. The results show that I cannot reject homoskedasticity for men or for the full sample because of small BPG test statistics. However, for women, we can reject homoscedasticity using the Koenker version of the Breusch-Pagan-Godfrey test.[5]

The R-squared and the adjusted R-squared values of these two specifications are almost the same, but suggest that specification (1) is a slightly better fit with the data for all individuals and for men. For women, the R-squared value of 0.219 for specification (1) means that the explanatory variables explain about 21.9 percent of the variation in the logarithm of wage. In specification (2), the R-squared values and adjusted R-squared values are both smaller than those in specification (1), which implies that attractiveness rated by interviewers at the start is more important in explaining the variance of earnings than attractiveness rated by interviewers at the end. Since the F-values are all relatively large, the models are significant overall.

[5] The standard errors in Table 4 are not robust to heteroskedasticity. However, when robust standard errors are calculated, the conclusions are same for all coefficient except for attractiveness as rated by interviewer at start and *heduc* .

In general, most of the estimated coefficients of the age variables are consistent with Pfeifer (2012), except for women in specification (2). In this specification, the estimated coefficient of *agesq* for women is significant at the 10% significance level, while in Pfeifer (2012), it is significant at 5% level. Moreover, the magnitudes of the estimated coefficients are smaller in Table 5 than in Pfeifer (2012). In particular, the estimated coefficient of age in years (*age*) for all individuals is 0.0499 in specification (1) and it is significant at the 1% significance level. The estimated coefficient of *age* for the male subsample, 0.0573, is larger than the estimated coefficient for the female subsample, 0.0362, is smaller. The estimated coefficient of *agesq* for all individuals in both specifications is -0.0442, and it is significant at the 1% significance level. It is smaller than the estimated coefficient for the male subsample, but larger than the estimated coefficient for the female subsample.

Because *age* has a positive effect on earnings, while *agesq* has a negative effect on earnings, the relationship between *age* and earnings has an inverted U-shape. I use the following equations to calculate the values of the turning points in the relationship:

(5.1)[6]

*age** is the value of *age* such that the log of earnings is increasing as long as *age* < *age**, and decreasing thereafter. In specification (1), the turning points are about 38 years old for the full sample, 35 years old for men and 40 years old for women. In specification (2), the results are identical.

The estimates for specification (2) are almost the same as those for specification (1). With respect to gender, the magnitudes of the estimated coefficients of *female* are much larger

[6] *agesq* is not the squared value of *age*, but equals the squared value of *age* divided by 100.

than in Pfeifer (2012). It is negative and significant at the 1% significance level in accordance with expectations. The estimated coefficient of *female* is -0.412 in specification (1) and -0.411 in specification (2).

As for the region where the interview was held (*EGermany*), the results are in accordance with Pfeifer (2012), except that the estimated coefficients for women are much smaller and the significance is slightly weaker. Specifically, in specification (1), the coefficient is -0.109 and it is significant at the 5% level. In specification (2), it is -0.102 and it is significant at the 5% level, too.

The estimated coefficients of the Body Mass Index (*BMI*) are insignificant for the full sample and for the female subsample. This result suggests that this proxy for health status has no effect on wages. However, for men, in specification (1), the coefficient is about 0.000984 and it is significant at the 1% significance level. In specification (2), it is 0.00101 and significant at the 5% significance level. The positive significance for men satisfies expectations.

As for marital status, the estimated coefficients are positive and significant for the full sample at the 5% significance level and for men at the 1% significance level, which implies that, on average, the earnings of married or previously married individuals are about 9 percent higher than those of never-married individuals. In addition, married or previously married men have about 26 percent higher earnings than those of never-married male individuals. This conclusion is inconsistent with my expectations. I think that one of the potential explanations for this result is that individuals who have spouses are considered by employers to take jobs more serious. Hence, employers pay them more. In the contrast, being married or was married is not an advantage for women, which is consistent with my expectations. From table 5, I find that in specification (1), the estimated coefficient of *mastatus* for women is -0.154 and it is significant at the 5% significance level. In specification (2), it is -0.139and it is significant at the 5% significance level.

With respect to the education variables, the results are broadly consistent with other studies that estimate human capital earnings models. The higher the education level, the higher is income on average, especially the estimates of *uasdegree* and *udegree*. The estimated coefficients of the education variables are positive and significant with the exception of that of *heduc*. More specifically, in specification (1), the estimated coefficient of *heduc* for the full sample is 0.0908 and it is significant at the 5% significance level. The estimated coefficient for women is 0.102 and it is significant at the 1% significance level. The estimated coefficient for men is 0.0778 but insignificant. In specification (2), the magnitudes of the estimated coefficients of *heduc* are slightly larger for the full sample and for men, but a bit smaller for women; most notably they are insignificant for both the male and female subsamples.

The estimation results for *uasdegree* and *udegree* are similar, although the estimated coefficients of *udegree* are larger than the estimated coefficients of *uasdegree*. They are all significant at the 1% significance level, and the results also show that both these education levels have greater effects on wages for women than for men. Moreover, for men the estimated coefficients are larger in specification (1), which implies that the education levels are more important in attractiveness as rated by interviewers at the start. For example, in specification (1), the estimated coefficient of *udegree* for men is 0.383 and the estimated coefficient for women is 0.447. In contrast, in specification (2), the estimated coefficient of *udegree* for men is 0.378 and the estimated coefficient for women is 0.452. I can infer that my results for education variables are reasonable, since they are consistent with the results of French (2000), who found that "earnings [were] a concave function of experience (age-education) and education was positive and statistically significant."

Turning attention to physical attractiveness, the results are slightly different from Pfeifer (2012). First of all, the estimated coefficients are positive and significant at the 1% significance level, while in Pfeifer (2012), the level of significance is weaker for women. In addition, for the full sample and for women, the first impression (attractiveness rated at the start of the interview) has a larger effect on the individuals' earnings, while the opposite is true for men. This result differs from Pfeifer (2012), who finds that the effect of the attractiveness on earnings is lower at the end of the interview for all samples. In general, if an employee gets one more point on the eleven-point-scale rating system, earnings rise by about 4.6%. In particular, in specification (1), the estimated coefficient for men is 0.0487, and the estimated coefficient for women is 0.0457. In contrast, in specification (2), the estimated coefficient for men is 0.0544 while the estimated coefficient for women is 0.0336.

Overall, I find that first impressions are more important than final impressions in explaining labour income, and that education levels are more important for women. However, physical attractiveness has lager impact on men than on women. But again, the differences are not large and the results of significance are identical to the results of the average marginal effects.

5.3 Log Earnings as a Non-Linear Function of Attractiveness

The next step of my analysis is to re-estimate the models including quadratic function of physical attractiveness. I add the square of each physical attractiveness variables. The new parameter estimates can be found in Table 6. Using the Jarque-Bera test I can reject the null hypothesis of normality in the error distribution. In addition, I find that heteroskedasticity exists for the full sample and for women. In the heteroskedasticity test, in specification (1), the Koenker version of the Breusch-Pagan-Godfrey test show that I can reject homoskedasticity while White's test implies that I cannot reject homoskedascity. In specification (2), both tests reject homoscedasticity.[7] For men, heteroskedasticity does not exist.

In the re-estimated models, each estimated coefficient still represents the nonlinear effect of the explanatory variable on the log of earnings. Compared with the simple models of section 5.2, the R-squared values and adjusted R-squared values are slightly larger. Hence, the goodness of fit of the new regressions is better than before. The F-values re smaller, but all the models are still significant overall. For example, for the full sample in specification (1) the R-squared value is 0.336, the adjusted R-squared value is 0.331, and the F-value is 64.86.

Most estimated coefficients of the explanatory variables are similar to those of the simple Ordinary Least Squares models discussed in the last section, except for the attractiveness variables. Considering the squared terms of attractiveness, the estimated coefficients are significant for all samples except for the female subsample in specification (1). For women, the estimated coefficient of attractiveness rated by the interviewer at the start

[7] When robust standard errors are computed, the coefficients of attractiveness as rated by interviewer at start for women are not significant at the common significance levels. The coefficient of *heduc* is not significant for women at the common significance levels.

is 0.130 and it is significant at the 5% significance level in specification (1). In specification (2), the estimated coefficient of attractiveness rated by the interviewers at the end is 0.159 and it is significant at the 5% significance level.

The parabolic slope of the relationship between log net labor income and attractiveness relies on the value of attractiveness. To gain more insight into this relationship, I take the derivatives of *lwage* with respect to the attractiveness variables:

(5.2)

(5.3)

These slopes are steeper for men than the slopes for women due to the larger magnitudes of the estimated coefficients for men. To be more specific, in specification (1) the estimated coefficient of *attstartsq* for men is -0.0142 and it is measured at -0.00556 for women. In specification (2), the estimated coefficient of *attstartsq* for men is -0.0226 and it is measured at -0.00836 for women. This implies that the figure for men is more concave and the figure is more concave in specification (1) than in specification (2).

In addition, Table 6 reports the average marginal effects of *attstart* and *attend* using equation (5.2) and (5.3), respectively. For the full sample and for women, the marginal effect of attractiveness in specification (1) is larger than those in specification (2). For example, for the full sample, one unit increase at attractiveness as rated by interviewer at the start, the log wage increase 3.9 percent. While one unit increase at attractiveness as rated by interviewer at the end, the log wage increase 3.5 percent. For women, one unit increase at attractiveness as rated by interviewer at the start, the log wage increase 4 percent. While one unit increase at attractiveness as rated by interviewer at the end, the log wage increase 2 percent. This result is not true for men. For men, one unit increase at attractiveness as rated by interviewer at the start, the log wage increase 4.2 percent. While one unit increase at attractiveness as rated by interviewer at the start, the log wage increase 4.6 percent.

In equation (5.1) and (5.2), the estimated parameters of the first terms and the second terms are respectively positive and negative. This implies that the corresponding graphs should be inverted U-shapes. The turning point (or maximum of *lwage*) is always achieved when attractiveness equals the coefficient of the attractiveness variable over twice the absolute value of the coefficient on the squared term. I use the following equations to calculate the values of the turning points in the relationship of *lwage* and attractiveness:

(5.4)

(5.5)

Before reaching the turning point, the log of earnings continues to increase with physical attractiveness, while after this turning point the log wage begins to decrease. It is easy to compute the values for the turning points using the estimates and equations (5.4) and (5.5). In specification (1), for all individuals the level of attractiveness at the turning point of the attractiveness at the beginning is 9.68, which is larger than the value of the turning point for specification (2), 9.17. For men, the value of attractiveness at the turning point is 9.19, which is larger than the value of the turning point for specification (2), 8.81. For women, the turning point is reached when the attractiveness at the beginning is 11.69, or when the attractiveness at the end is 9.51.

Notably, in specification (1), for women the predicted level of attractiveness at the turning point exceeds eleven, which means this turning point does not exist. If we plot earnings quadratic-form regression, I foresee the figure of the female respondents will tend to be monotonically increasing slowly. From this I deduce that, in the eleven-point scale system for attractiveness, the prettier the female employee, the higher wage she can get at least in specification (1). On the other hand, a good-looking man receives a higher wage too, but a man with outstanding looks may face a wage penalty.

Using the parameter estimates in Table 6, I plot the relationship between attractiveness and earnings in Figure 1 for men and Figure 2 for women. Consistent with the figures of Pfeifer (2012), the graph for men is more concave than the graph for women and look like an inverse U-shape because the earnings equation is in quadratic form. I use the concavity of the figures to compare the effects of the earning premium for the individuals at different beauty levels. Some economists, such as Hamermesh and Biddle (1994), Biddle and Hamermesh (1998) and Mobius and Rosenblat (2006) suggest that there should be a punishment for unattractive people, while a premium exists for attractive people. The concavity shows that the income punishment for levels of attractiveness below the sample mean is larger than the income premium for levels attractiveness above the mean. The graph for men is much more concave than the graph for women. This finding is consistent with those of Hamermesh and Biddle (1994), Biddle and Hammermesh (1998) and Mobius and Rosenblat (2006), Thus my estimates imply a punishment for both a lack of beauty and outstanding appearance.

6. Comparisons and Conclusions

This paper focuses on the relationship between labour market outcomes, physical attractiveness and education using German survey data from ALLBUS 2008. With a different sample, I examine whether the conclusions of Pfeifer (2012) hold or not. Nonetheless, most of the estimations are consistent with those of previous studies although departures exist. For the earnings sample, I find that the estimates of two specifications are identical while the marginal effects of physical attractiveness rated by interviewers at the start are smaller than the marginal effects of physical attractiveness rated by interviewers at the end. All the marginal effects of physical attractiveness are positive and significant for men and for women. Additionally, the marginal effects of physical attractiveness are larger for men than for women.

In linear models for the earnings sample, two findings of Pfeifer (2012) hold for my samples. First of all, due to relatively larger R-squared values and adjusted R-squared values, physical attractiveness rated by interviewers at the end can explain the variance of earnings better. Secondly, the slopes of estimated coefficients of attractiveness are larger for men than for women. Pfeifer (2012) argues that in the earnings sample, the rates of return of physical attractiveness rated by interviewers at the start are larger than the rates of return of physical attractiveness rated by interviewers at the end. However, I find that it does not hold for men in my earnings sample. In non-linear models, the results in this paper confirm that the wage punishment for below-average attractiveness is more serious than the wage premium for above-average attractiveness. I find that the attractiveness-earnings profiles are consistent with those in Pfeifer (2012) as well, in which the plots for men are steeper than for women and the graph of women appear linear.

There are two notable innovations to successfully show that that punishment for outstanding looks exists, especially for men. The first innovation is that I use marginal effects at the representative values of most unattractiveness and most attractiveness in my probit models to illustrate the differences across extreme attractiveness levels. The second one relates to the turning points of physical attractiveness for OLS regression models, and I find that for male individuals, before attractiveness ratings reach nine, earnings rise with attractiveness. After nine, the earnings diminish with attractiveness. But this trend does not hold for women with physical attractiveness rated by interviewers at the start. It seems that the better the first impressions, the higher wages females get.

Due to the limitations of the data set in this paper, I did not show the interaction effects between physical attractiveness and education in affecting labour market outcomes. I planned to examine the interaction terms between physical attractiveness and education levels and found that they were too highly correlated with the original education variables. The estimations failed to show the interaction effects between those two factors because there are big and unexpected changes on magnitudes of coefficients of *uasdegree* and *udegree*. Therefore, I dropped the interaction terms. I think further study is needed in this area.

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Table 1. Sample Means for Probit Models of Employment Status

	All (n=2764)	Men (n=1416)	Women (n=1348)
employment	0.5669	0.5946	0.5378
attstart	7.3658	7.2415	7.4963
attend	7.4783	7.3588	7.6039
heduc	0.2844	0.3121	0.2552
uasdegree	0.0626	0.0833	0.0408
udegree	0.1266	0.1434	0.1091
age	51.4121	50.5184	52.3509
agesq	29.5224	28.5020	30.5943
female	0.4877	0.0000	1.0000
EGermany	0.3343	0.3220	0.3472
BMI	65.4906	65.2698	65.7225
married	0.5749	0.6179	0.5297
marriedapart	0.0170	0.0155	0.0185
widowed	0.0926	0.0381	0.1499
divorced	0.0890	0.0720	0.1068
nevermarried	0.2265	0.2564	0.1951
religion1	0.3119	0.2867	0.3383
religion2	0.0076	0.0092	0.0059
religion3	0.2753	0.2669	0.2841
religion4	0.0210	0.0212	0.0208
religion5	0.0293	0.0403	0.0178
religion6	0.3549	0.3757	0.3331

Table 2. Sample Means for the Earnings Sample

	All (n=1422)	Men (n=804)	Women (n=618)
Log of wage	7.2410	7.4111	7.0196
Attractiveness-rated by interviewer at start	7.8572	7.6965	8.0663
Attractiveness-rated by interviewer at end	7.9494	7.7985	8.1456
Female(Dummy)	0.4346	0.0000	1.0000
High education(Dummy)	0.3481	0.3458	0.3511
University of Applied Sciences degree(Dummy)	0.0752	0.0871	0.0599
University degree(Dummy)	0.1624	0.1580	0.1683
Age in years	42.6892	42.5323	42.8932
Age squared/100	19.6344	19.5789	19.7068
East Germany(Dummy)	0.2954	0.2749	0.3220
Body Mass Index	65.9975	65.0147	67.2761
Marrital Status(Dummy)	0.7124	0.68781	0.7443

Table 3. Marginal Effects for Probit Models of Employment Status

	Specification (1)			Specification (2)		
	All	Men	Women	All	Men	Women
attstart	0.0193***	0.0201***	0.0184***			
	(0.0037)	(0.0052)	(0.0053)			
attend				0.0226***	0.0240***	0.0197***
				(0.0037)	(0.0052)	(0.0053)
heduc	-0.0261	-0.0454*	0.00378	-0.0254	-0.0424	0.00268
	(0.0194)	(0.0261)	(0.0289)	(0.0193)	(0.0260)	(0.0289)
uasdegree	0.0950***	0.133***	0.034	0.0915***	0.126***	0.036
	(0.0334)	(0.0428)	(0.0539)	(0.0333)	(0.0425)	(0.0540)
udegree	0.148***	0.166***	0.126***	0.144***	0.161***	0.124***
	(0.0269)	(0.0353)	(0.0417)	(0.0269)	(0.0353)	(0.0419)
age^3	-0.0115***	-0.0140***	-0.00884***	-0.0115***	-0.0139***	-0.00888***
	(0.0006)	(0.0008)	(0.0009)	(0.0006)	(0.0008)	(0.0009)
female	-0.0363***			-0.0376***		
	(0.0140)			(0.0140)		
EGermany	-0.0734***	-0.113***	-0.0328	-0.0720***	-0.110***	-0.0331
	(0.0178)	(0.0247)	(0.0255)	(0.0178)	(0.0247)	(0.0254)
BMI	0.000177	0.000209	0.000201	0.000201	0.000253	0.000204
	(0.0002)	(0.0003)	(0.0003)	(0.0002)	(0.0003)	(0.0003)
married but living apart	-0.136***	-0.0375	-0.193***	-0.137***	-0.0449	-0.193***
	(0.0523)	(0.0761)	(0.0674)	(0.0523)	(0.0768)	(0.0676)
widowed	-0.0492	-0.0307	-0.0671	-0.0513	-0.0383	-0.0674
	(0.0346)	(0.0583)	(0.0436)	(0.0346)	(0.0592)	(0.0434)
divorced	-0.0642***	-0.0796**	-0.0545*	-0.0587**	-0.0717**	-0.0518
	(0.0240)	(0.0364)	(0.0317)	(0.0240)	(0.0365)	(0.0317)
never married	-0.0595***	-0.101***	-0.019	-0.0568***	-0.0954***	-0.0204
	(0.0215)	(0.0284)	(0.0316)	(0.0215)	(0.0286)	(0.0316)
religion1	0.0113	0.00145	0.0245	0.0103	-0.000737	0.0238
	(0.0192)	(0.0270)	(0.0272)	(0.0191)	(0.0269)	(0.0271)
religion2	-0.0275	0.0101	-0.0604	-0.013	0.0221	-0.0478
	(0.0813)	(0.1110)	(0.1210)	(0.0815)	(0.1110)	(0.1220)
religion3	0.00297	-0.0165	0.0234	0.00323	-0.0162	0.0234
	(0.0211)	(0.0296)	(0.0300)	(0.0211)	(0.0295)	(0.0300)
religion4	-0.0433	-0.0546	-0.0145	-0.0449	-0.0595	-0.0159
	(0.0493)	(0.0682)	(0.0716)	(0.0492)	(0.0677)	(0.0718)

religion5	-0.144***	-0.226***	0.0479	-0.144***	-0.224***	0.0466
	(0.0372)	(0.0444)	(0.0736)	(0.0372)	(0.0443)	(0.0739)
Observations	2764	1416	1348	2764	1416	1348
Predictive Margins	0.5676	0.5970	0.5378	0.5679	0.5970	0.5382
Pseudo R^2	0.43	0.432	0.443	0.432	0.435	0.443
Log likelihood	-1077.9557	-543.0747	-518.7103	-1073.2207	-540.0603	-517.9369
LR chi2	1626.1	825.8	823.6	1635.6	831.8	825.1

Notes:

1. Standard errors in parentheses.

2. Coefficients are significant at *10%, **5%, and ***1%.

3. This is the combined marginal effect of *age* and *agesq*.

Table 4. Marginal Effects for Most Unattractive and Most Attractive Individuals

	Specification (1)			Specification (2)		
	All	Men	Women	All	Men	Women
attstart						
most unattractive	0.0226***	0.0238***	0.0212***			
	(0.0046)	(0.0066)	(0.0064)			
most attractive	0.0176***	0.0180***	0.0170***			
	(0.0030)	(0.0040)	(0.0045)			
attend						
most unattractive				0.0267***	0.0288***	0.0228***
				(0.0046)	(0.0066)	(0.0064)
most attractive				0.0202***	0.0209***	0.0181***
				(0.0029)	(0.0038)	(0.0044)
heduc						
most unattractive	-0.0306	-0.0537*	0.00435	-0.03	-0.0509	0.0031
	(0.0227)	(0.0310)	(0.0333)	(0.0228)	(0.0312)	(0.0334)
most attractive	-0.0237	-0.0405*	0.00349	-0.0226	-0.0369	0.00247
	(0.0176)	(0.0233)	(0.0267)	(0.0172)	(0.0226)	(0.0266)
uasdegree						
most unattractive	0.111***	0.157***	0.0393	0.108***	0.151***	0.0416
	(0.0390)	(0.0504)	(0.0621)	(0.0392)	(0.0506)	(0.0624)
most attractive	0.0864***	0.119***	0.0315	0.0816***	0.109***	0.0331
	(0.0306)	(0.0386)	(0.0499)	(0.0299)	(0.0374)	(0.0497)
udegree						
most unattractive	0.174***	0.197***	0.145***	0.170***	0.193***	0.143***
	(0.0310)	(0.0412)	(0.0475)	(0.0313)	(0.0417)	(0.0478)
most attractive	0.135***	0.148***	0.116***	0.128***	0.140***	0.114***
	(0.0249)	(0.0325)	(0.0391)	(0.0245)	(0.0317)	(0.0391)
Observations	2764	1416	1348	2764	1416	1348
Pseudo R^2	0.43	0.432	0.443	0.432	0.435	0.443
chi2	1626.1	825.8	823.6	1635.6	831.8	825.1

Notes:

1. Standard errors in parentheses.
2. Coefficients are significant at *10%, **5%, and ***1%.
3. Derived from probit models of employment status.

Table 5. OLS Estimates of Earnings Models: Linear in Attractiveness

	Specification (1)			Specification (2)		
	All	Men	Women	All	Men	Women
attstart	0.0458***	0.0487***	0.0457***			
	(0.0082)	(0.0110)	(0.0117)			
attend				0.0455***	0.0544***	0.0336***
				(0.0085)	(0.0116)	(0.0120)
heduc	0.0908**	0.0778	0.102*	0.0923**	0.084	0.0956
	(0.0408)	(0.0549)	(0.0583)	(0.0408)	(0.0547)	(0.0587)
uasdegree	0.272***	0.219***	0.305***	0.272***	0.218***	0.316***
	(0.0608)	(0.0765)	(0.0967)	(0.0609)	(0.0764)	(0.0972)
udegree	0.414***	0.383***	0.447***	0.410***	0.378***	0.452***
	(0.0504)	(0.0673)	(0.0724)	(0.0505)	(0.0672)	(0.0730)
age	0.0499***	0.0573***	0.0362***	0.0498***	0.0584***	0.0348***
	(0.0081)	(0.0103)	(0.0124)	(0.0081)	(0.0103)	(0.0125)
agesq	-0.0442***	-0.0530***	-0.0282**	-0.0442***	-0.0539***	-0.0274*
	(0.0093)	(0.0118)	(0.0142)	(0.0093)	(0.0118)	(0.0143)
female	-0.412***			-0.411***		
	(0.0291)			(0.0291)		
EGermany	-0.246***	-0.351***	-0.109**	-0.238***	-0.341***	-0.102**
	(0.0316)	(0.0428)	(0.0446)	(0.0315)	(0.0425)	(0.0448)
BMI	0.000102	0.000984*	-0.000819	0.000133	0.00101**	-0.000812
	(0.0004)	(0.0005)	(0.0006)	(0.0004)	(0.0005)	(0.0006)
mastatus	0.0859**	0.255***	-0.154**	0.0874**	0.248***	-0.139**
	(0.0403)	(0.0523)	(0.0605)	(0.0404)	(0.0523)	(0.0605)
Constant	5.682***	5.387***	5.727***	5.679***	5.310***	5.856***
	(0.1770)	(0.2270)	(0.2720)	(0.1790)	(0.2320)	(0.2730)
Observations	1422	804	618	1422	804	618
R^2	0.33	0.349	0.219	0.328	0.351	0.21
Adjusted R^2	0.325	0.342	0.208	0.324	0.344	0.198
F	69.41	47.29	18.97	68.99	47.7	17.94
LM JB Normality test	3.30E+04	5.20E+04	12.3460	3.20E+04	5.20E+04	11.3545
LM JB P-Value	0.0000	0.0000	0.0021	0.0000	0.0000	0.0034
BPG test	15.45	13.34	17.67	15.07	13.05	17.55
BPG P-value	0.1164	0.148	0.0392	0.1297	0.1603	0.0407
White's test	66.87	52.91	58.69	66.43	51.45	55.98
White's P-value	0.1987	0.2903	0.1179	0.2092	0.3403	0.1733

Notes: Log-linear net labor income functions with the simple OLS model, coefficents. Standard errores in parentheses. Coefficients significant at *10%, **5%, and ***1%

Table 6. OLS Estimates of Earnings Models: Non-Linear in Attractiveness

	Specification (1)			Specification (2)		
	All	Men	Women	All	Men	Women
attstart	0.209***	0.261***	0.130**			
	(0.0454)	(0.0618)	(0.0641)			
attstartsq	-0.0108***	-0.0142***	-0.00556			
	(0.0030)	(0.0041)	(0.0042)			
attend				0.264***	0.398***	0.159**
				(0.0497)	(0.0766)	(0.0626)
attendsq				-0.0144***	-0.0226***	-0.00836**
				(0.0032)	(0.0050)	(0.0041)
heduc	0.0893**	0.0788	0.0999*	0.0961**	0.0881	0.0982*
	(0.0406)	(0.0546)	(0.0583)	(0.0406)	(0.0540)	(0.0585)
uasdegree	0.275***	0.226***	0.303***	0.276***	0.224***	0.317***
	(0.0606)	(0.0760)	(0.0966)	(0.0605)	(0.0755)	(0.0970)
udegree	0.411***	0.376***	0.447***	0.406***	0.372***	0.449***
	(0.0502)	(0.0668)	(0.0723)	(0.0502)	(0.0664)	(0.0728)
age	0.0511***	0.0579***	0.0375***	0.0499***	0.0576***	0.0354***
	(0.0081)	(0.0102)	(0.0124)	(0.0080)	(0.0102)	(0.0124)
agesq	-0.0456***	-0.0536***	-0.0296**	-0.0439***	-0.0524***	-0.0280**
	(0.0092)	(0.0118)	(0.0142)	(0.0092)	(0.0117)	(0.0142)
female	-0.407***			-0.401***		
	(0.0290)			(0.0290)		
EGermany	-0.241***	-0.347***	-0.106**	-0.234***	-0.344***	-0.0960**
	(0.0315)	(0.0426)	(0.0446)	(0.0313)	(0.0420)	(0.0448)
BMI	0.000166	0.00104**	-0.000776	0.000221	0.00105**	-0.000724
	(0.0004)	(0.0005)	(0.0006)	(0.0004)	(0.0005)	(0.0006)
mastatus	0.0800**	0.244***	-0.156**	0.0752*	0.225***	-0.145**
	(0.0402)	(0.0520)	(0.0604)	(0.0402)	(0.0519)	(0.0605)
Constant	5.079***	4.630***	5.400***	4.886***	4.080***	5.392***
	(0.2420)	(0.3130)	(0.3650)	(0.2520)	(0.3550)	(0.3540)
Observations	1422	804	618	1422	804	618
R^2	0.336	0.359	0.222	0.338	0.367	0.215
Adjusted R^2	0.331	0.351	0.209	0.333	0.359	0.202
F	64.86	44.38	17.27	65.36	46.05	16.65
LM JB Normality test	3.30E+04	5.20E+04	13.3238	3.30E+04	5.20E+04	13.17592
LM JB P-Value	0.0000	0.0000	0.0013	0.0000	0.0000	0.0014
BPG test	18.26	14.69	26.70	17.87	14.88	24.15
BPG P-value	0.0758	0.1438	0.0029	0.0846	0.1366	0.0072
White's test	72.31	57.81	93.48	72.54	55.86	92.57

White's P-value	0.3693	0.4824	0.0017	0.362	0.5554	0.002
Marginal effect of attstart	0.0385	0.0420	0.0404			
Marginal effect of attend				0.0347	0.0463	0.0232

Notes:

1. Log-linear net labor income functions with the OLS model in quadratic form, coefficents. Standard errores in parentheses. Coefficients significant at *10%, **5%, and ***1%
2. The marginal effects of *attstart* and *attend* are average marginal effects for the sample.

Figure 1. Attractiveness and Earnings for Men

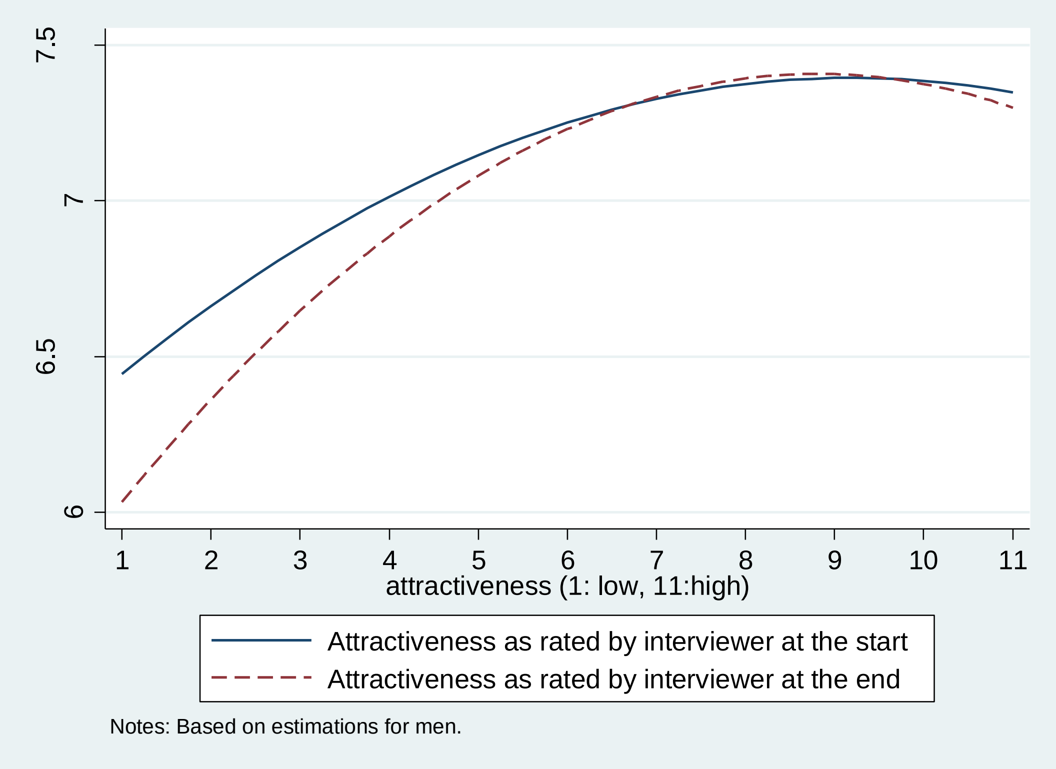

Figure 2. Attractiveness and Earnings for Women

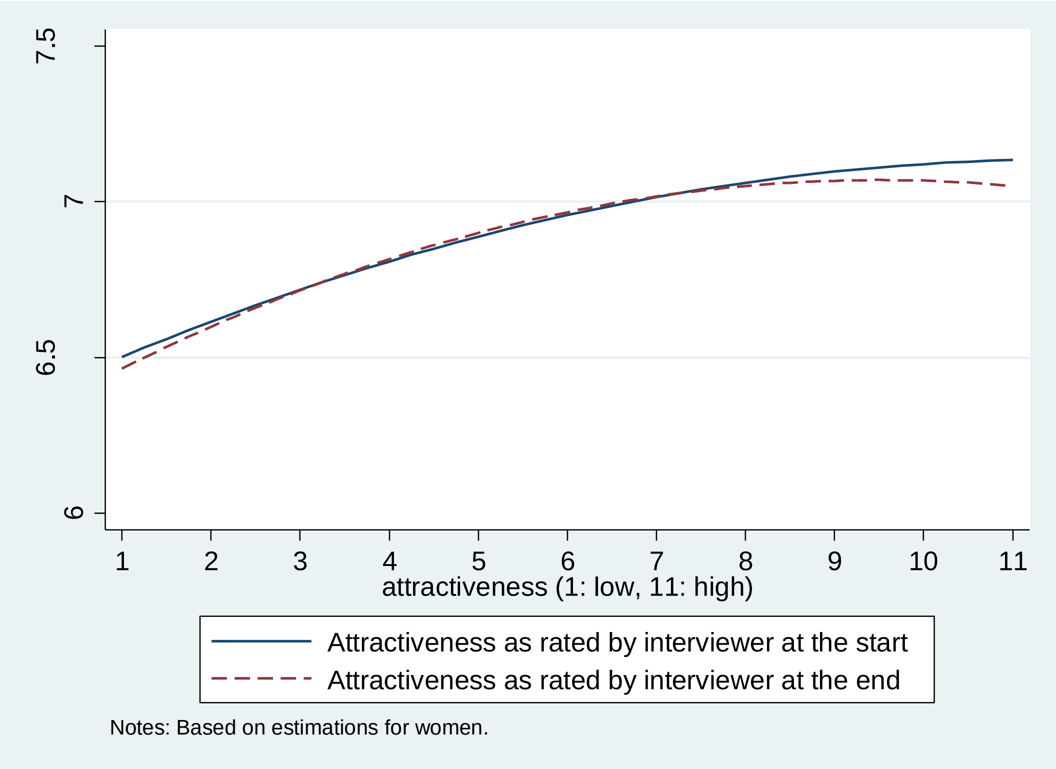

Table A1. ALLBUS Variables Used

	Variable Label
V2	YEAR
V5	REGION OF INTERVIEW: WEST - EAST
V450	BODY-MASS-INDEX
V554	AGE
V556	SEX
V563	GENERAL SCHOOL LEAVING CERTIFICATE
V557	RESPONDENT: RELIGIOUS DENOMINATION
V579	UNIV. OF APPLIED SCIENCES DEGREE
V580	UNIVERSITY DEGREE
V583	CURRENT EMPLOYMENT STATUS
V677	HOURS WORKED PER WEEK
V707	NET INCOME
V737	MARITAL STATUS
V1542	ATTRACTIVENESS OF R., START OF INTERVIEW
V1543	ATTRACTIVENESS OF R., END OF INTERVIEW

Table A2.Allocation of Variables to Models

Name	Definition	Earning Sample	Employment Sample
attstart	The attractiveness as rated by the interviewer at the start.	√	√
attend	The attractiveness as rated by the interviewer at the end.	√	√
heduc	A dummy variable for general school leaving certificate.	√	√
usadegree	A dummy variable for university of applied sciences degree.	√	√
udegree	A dummy variable for university degree.	√	√
age	The age of the interviewee in years.	√	√
agesq	The squared value of *age*/100.	√	√
female	A dummy variable for sex of the interviewee.	√	√
EGermany	A dummy variable for region of the interview.	√	√
BMI	Body Mass Index	√	√
mastatus	Marital status of interviewee.	√	
married and cohabiting	One of the marital statuses of interviewee.		
married but living apart	One of the marital statuses of interviewee.		√
widowed	One of the marital statuses of interviewee.		√
divorced	One of the marital statuses of interviewee.		√
never married	One of the marital statuses of interviewee.		√
religion1	German Protestant church.		√
religion2	Protstant free church.		√
religion3	Roman Catholic church.		√
religion4	Another Christian denomination.		√
religion5	Non-Christian denomination.		√
religion6	Non-affiliation.		
attstartsq	The squared value of *attend* / 100.	√	
attendsq	The squared value of *attstart* /100.	√	
employment	The employment status indicator.		√
lwage	The logarithm of annual wage.	√	