Direct and Indirect Effects of Noncognitive Skills on the Gender Wage Gap*

Dimitrios Nikolaou†
The Ohio State University

October, 2012

Abstract

Prior research finds that noncognitive skills have a moderate effect on gender wage differences. I ask if existing studies underestimate this effect because noncognitive skills affect worker productivity (the direct effect) and occupational choice (the indirect effect). Using data from the National Child Development Study and jointly modeling gender-specific occupational attainment and wage determination, I find that the magnitude of the contribution of noncognitive skills to the gender wage gap is underestimated by 18 percentage points when the indirect effect is overlooked. I also show that this contribution differs with age. At age 33, women *directly* benefit because of higher productivity in noncognitive skills, while, at age 50, women benefit *indirectly* because they have sorted into occupations that reward these skills. I conclude that noncognitive skills are indeed significant for explaining the gender wage gap, particularly among mid-career workers.

JEL Classification: J24, J31
Keywords: Noncognitive Skills, Gender Wage Gap, Occupational Choice, U.K.

---

*I am greatly indebted to Audrey Light for her constant support and guidance. I also thank Bruce Weinberg, Randy Olsen and participants in the applied microeconomics workshop at The Ohio State University for valuable suggestions. All remaining errors are my own.

†Email: nikolaou.1@osu.edu; Department of Economics, The Ohio State University, Arps Hall 410, 1945 N. High St., Columbus, OH, 43210-1172.

1 Introduction

Despite substantial increases in female schooling and labor force participation in the last three decades, gender wage disparity persists (*e.g.*, Acemoglu and Autor 2011). In the United Kingdom, for example, women are paid, on average, 17% less than similarly educated and experienced men (Office of National Statistics 2011). Apart from education and experience, prior research examined gender differences in noncognitive traits as an additional explanation for male-female wage differences, and reported only a moderate effect of these traits on the predicted gender wage gap (*e.g.*, Cobb Clark and Tan 2011; Fortin 2008; Mueller and Plug 2006). However, this moderate effect is counter-intuitive, as noncognitive skills are associated with a wide array of economic outcomes including labor market productivity and occupational choice (*e.g.*, Almlund *et al.* 2011) and can be equally important as cognitive skills (*e.g.*, Brunello and Schlotter 2011; Heckman, Stixrud and Urzua 2006). In the current paper, I ask if existing studies underestimate the effect of noncognitive traits on the gender wage gap because they impose the assumption that noncognitive traits affect workers' wages identically across occupational sectors.

The innovation of this paper is that I allow noncognitive traits to affect gender differences in wages through two potential mechanisms. First, noncognitive traits are valued in the labor market and are *directly* rewarded by employers. If men and women have different levels of noncognitive traits, they will be paid differently even if they have similar jobs. Second, noncognitive traits make workers more qualified to enter specific occupations, which *indirectly* affect wages. Stated differently, noncognitive traits influence the distribution of men and women across different occupations and, in turn, affect wages. Previous studies that do not distinguish between these two effects identify the total effect of interest, which captures how the gender wage gap changes due to the impact of noncognitive traits on productivity (the direct effect) and on preference-based choices (the indirect effect). This leads to the question: is the contribution of noncognitive traits to the gender wage gap underestimated when endogenous selection into occupations is overlooked?

To address this question, I identify the direct, indirect, and total effects of noncognitive traits on the gender wage gap using data for U.K. workers from the National Child Development Study (NCDS). I estimate gender-specific wage models unconditional on occupation, but conditional on noncognitive and cognitive traits, to capture their total effect on wages. Because the effect of noncognitive traits can vary across occupations, I jointly model gender-specific occupational attainment and wage determination to identify the direct effects of noncognitive traits on wages. As exclusion restrictions in the occupational choice model I use the paternal socioeconomic status at age 16, and the within occupational group change in female-to-male employment ratio. Under this specification, the direct effect will capture the effect of noncognitive traits net of occupational sorting effects. The difference between the total and the direct effect will show how much of the wage effect is due to occupation-specific returns to noncognitive traits. I assess the contribution of these traits to the gender wage gap with a Oaxaca wage decomposition because the degree of gender differences in wages is determined both by gender differences in trait prices across occupations and by gender differences in traits among workers who select into the same occupation. I apply this wage decomposition to the two-stage method in order to identify the direct effect of noncognitive traits on the gender wage gap, while the indirect effect is calculated as the difference in the decomposition methods for the total and direct effects.

I proxy noncognitive traits using test scores on the Big Five taxonomy, which includes measures on openness to experience, conscientiousness, extraversion, agreeableness, and neuroticism. For cognitive skill measures, I use scores on standardized math and reading tests. To address that wages may affect noncognitive and cognitive skills, I measure them as traits that the workers acquire before they enter the labor market at late adolescence (age 16). For similar reasons, I measure schooling attainment at early adulthood (age 23), before wages are measured in my analysis (age 33 and age 50). I choose to treat noncognitive and cognitive skills as predetermined to allow for more direct comparison with previous studies that treat occupation as randomly chosen, while I treat fertility and schooling as predetermined because most of these decisions have already been made at ages 33 and 50.

To assess how much accounting for worker heterogeneity across occupations matters for understanding the role of noncognitive traits on the male-female wage gap, I show how the inferences would have changed in alternative models that do not consider the mechanism of occupational sorting. That is, I directly replicate the findings of three studies that have reported a moderate (*e.g.*, Fortin 2008; Mueller and Plug 2006) or an insignificant (*e.g.*, Cobb-Clark and Tan 2011) effect of the traits of interest, and compare them with results under endogenous selection into occupations.

The main finding in my paper is that the magnitude of the contribution of noncognitive traits to the gender wage gap is underestimated by 18 percentage points when the indirect effect on wages due to selection into occupations is ignored. This effect is non-negligible, and can be comparable to the entire portion of the gender wage gap that is explained by cognitive skills. I also show that the contribution of noncognitive traits to the gender wage gap differs with age. At age 33, I find that differences in endowments in noncognitive traits decrease male-female wage differences, which suggests that women *directly* benefit because of higher productivity in these traits. Compensating women for differences in prices in noncognitive traits would leave the gap relatively unchanged. At age 50, I find that differences in returns to these endowments close the gender wage gap, suggesting that women benefit *indirectly* because they have sorted into occupations that reward their noncognitive traits. Additionally, the decline in the male-female wage differential over the career (by 0.054 log points or 16%) can be largely explained—apart from occupational sorting—by the decline in gender differences in experience (24.1%) and in full-time employment (12.3%).

I contribute to the literature on the gender wage gap in two ways. First, I examine the importance of noncognitive traits on the gender wage gap by accounting for their effect on occupational sorting. This method allows me to more accurately assess their role in explaining male-female wage differentials because I capture occupation-specific trait heterogeneity. Using this indirect channel, I can explain why previous studies, which pool workers across occupations, do not find large effects (*e.g.*, Cobb Clark and Tan 2011; Fortin 2008; Mueller and Plug 2006). Second, by jointly modeling occupational choice and wage determination in two different periods of the working life, I quantify which factors are important for the change of the gender wage gap across time. With my analysis, I complement previous studies that have examined the growth of the gender wage gap for early career workers (Cattan 2012) with mature workers at their fifties, and for an alternative country than the U.S. To my knowledge, my paper is the first to identify the direct and indirect effects of noncognitive skills on the gender wage gap for the case of the U.K. by incorporating the link among noncognitive skills, occupational attainment and the gender wage gap.

My finding that pre-labor market traits have lasting effects (as they narrow the gender wage gap), contributes to policy discussions about pathways to deal with gender inequality. Early investments in noncognitive traits might have a dual beneficial effect. On the one hand, they will boost performance in standardized cognitive tests and lead to improved educational outcomes (*e.g.*, Heckman, Stixrud and Urzua 2006), both of which narrow the gender wage gap. On the other hand, because noncognitive traits stabilize during adolescence, and not during childhood as cognitive skills (*e.g.*, Almlund *et al.* 2011; Borghans *et al.* 2008), policies that aim at tackling gender wage inequality can invest in stimulating their development over longer periods of time.

2 Literature Review

In this section, I describe the few prior studies that have addressed total and direct effects of noncognitive traits on the gender wage gap. I also give more details on the three studies with which I will compare my findings in the results section, in order to assess how their results would have changed if the effects of noncognitive traits on occupational choice had not been ignored from their analysis.

Due to gender differences in noncognitive skills, some studies explore the *total* effects of noncognitive traits on the gender wage gap, though the magnitude of their contribution to the gap is contingent on the methodology employed. Mueller and Plug (2006) study the role of cognitive and noncognitive skills (measured by the Big Five traits) on gender wage differences for age 50 workers in the U.S. and find that only 3% of the gap is explained by differences in noncognitive skills including differences in endowments and differences in prices. This is a small effect considering that they use contemporaneous measures of noncognitive skills. I use their study as a comparison to directly show that heterogeneous effects of noncognitive skills on wages and occupational choice explain Mueller and Plug's small noncognitive skills effects. Fortin (2008) examines a younger cohort of U.S. workers from the NLSY79 at age 32. Using an alternative decomposition method to the Oaxaca decomposition in order to analyze the effects of noncognitive traits like altruism and ambition, she reports that 8.4% of the gender wage gap is explained by differences in the endowments of these noncognitive traits. I will use Fortin's analysis to show that endogenous selection into occupations is important even under alternative decomposition methods. Similar findings have been documented for Russia (Semykina and Linz 2007), while for Denmark (Nyhus and Pons 2012) and Germany (Braakman 2009) the effects are slightly higher—differences in endowments in noncognitive skills explain 11.2% and 11.5% of gender wage differentials, respectively.

Evidence on the *indirect* effects of interest has proven elusive. Information comes from studies on occupational attainment that do not address the subsequent contribution of noncognitive skills to the gender wage gap. For example, men who are in control of their life are more likely to be employed in high paying occupations compared to men who score low in locus of control (Andrisani 1977), and men high in leadership skills are more prone to entering managerial positions relative to men with less leadership skills (Kuhn and Weinberger 2005). Extraversion increases the probability of employment in sales (Filer 1986) or occupations that require more social interactions (Jackson 2006; Krueger and Schkade 2008).

The only study that incorporates direct and indirect effects of noncognitive traits on wages is Borghans, ter Weel and Weinberg (2008) who show that these effects are downward biased if their indirect effects on occupational choice are not accounted for. They conclude that workers are assigned to occupations in order to match their noncognitive skills (being caring and direct) with the job requirements; relatively more caring workers end up in occupations where this trait is more highly valued, and more sociable workers choose occupations associated with more social interactions. I build on this study by showing that the effects of noncognitive skills on the gender wage gap are also underestimated if their indirect effects on this gap are ignored.

The idea that noncognitive skills can affect wages and the worker's propensity to enter into occupations is the focus in Cobb-Clark and Tan (2011). They examine the relationship between personality traits, occupational attainment, and the gender wage gap, and find that noncognitive skills are not a significant contributor to the gender wage gap. Even though they argue that this finding is not due to ignoring the role of noncognitive skills on occupational assignment but partly due to lack of measures on cognitive skills, their results may be driven by their decomposition method which does not treat occupation as endogenous and, thus, they cannot distinguish between direct and indirect effects. I improve upon their study by explicitly controlling for cognitive skill measures and treating occupation as endogenous.

The only study that has examined the direct and indirect effects of noncognitive skills on the gender wage gap is Cattan (2012). She jointly models education, fertility, labor supply and occupational choice to assess the contribution of pre-labor market cognitive and noncognitive traits to male-female wage differences and to the growth in this wage gap. Using data from the NLSY79, and measuring noncognitive traits as behavioral problems and self-confidence, she finds that sorting into occupations is significant. Heterogeneity of wage returns in self-confidence and cognition can explain almost half of the gender wage gap at both age 25 and age 40. Cattan further reports an age difference; the returns of predetermined traits do not explain the increase in the gender wage gap between 25 and 40 years (by 6.4 log points), but the changes in the returns to education and experience account for all of the change in the gender wage gap. Women with higher education decreased their participation in the market and in certain occupations, which accounts for the growth in the gap during the early career. I complement this paper by focusing not on the early career, but on mid-career workers. For my sample of more mature workers, the fertility and the schooling investments are more likely to have been made, hence, my focus is on the indirect effect of noncognitive traits through occupational choice.

3 Empirical Framework

3.1 Total Effects of Noncognitive Skills on Wages

Given my interest in gender differences in wage determination, I estimate log earnings equations separately for men and women as:

$$lnW_{ig} = \delta_{0g} + \delta_{1g}NCS_{ig} + \delta_{2g}X_{ig} + v_{ig} \tag{1}$$

where the subscripts i and g denote individuals and gender, respectively. W_{ig} stands for wages, NCS_{ig} is a vector of variables representing noncognitive traits (namely personality traits), and v_{ig} is an error term with zero mean. Because the education path one will follow determines worker productivity (*e.g.*, Keane and Wolpin 1997) and because workers who accumulate work experience in a longer period of time are likely to earn less than continuously employed workers (*e.g.*, Light and Ureta 1995), I include in X_{ig} years of schooling and actual experience. The vector X_{ig} also includes measures of cognitive skills, demographic characteristics and job market characteristics, but not the occupational sector of the worker. Under this specification, δ_{1g} will capture the effect of noncognitive skills on gender-specific wages, unconditional on occupation, which is the *total* effect of interest. The results from this estimation method will serve as the baseline estimates for comparison with previous studies on the role of noncognitive skills on male-female wage differences.

3.2 Direct and Indirect Effects of Noncognitive Skills on Wages

Workers choose occupations, as opposed to being randomly assigned, in order to achieve a better match between their noncognitive traits and the chosen occupation. For instance, returns to sociability may be greater for a salesperson than an administrative worker inducing the more sociable workers to choose occupations where the returns to their noncognitive traits are higher. Similarly, more agreeable workers may receive lower returns because agreeableness is a trait that is not rewarded in the market, or because the more agreeable workers sort into the lower paying occupations. To address this endogeneity problem, I model occupation as a separate process that depends on noncognitive and cognitive skills, observed individual characteristics, job characteristics and unobserved preferences for occupational status.

Each worker chooses an occupation from a choice set $\{1, 2...J\}$. Each occupation j is determined by the employer's willingness to hire the worker and this willingness is, in turn, determined by the worker's productivity-related characteristics S. Moreover, each occupation offers a combination of wages w and occupation amenities a. For any given worker and at any given point in time, amenities increase utility ($u^{'}(\alpha) > 0$) but they decrease wages ($u^{'}(w) < 0$). That is, workers are willing to accept lower wages for desirable job characteristics but they need to be compensated for undesirable job characteristics. Then, a worker will weight the benefits from choosing an occupation such as potential earnings and nonpecuniary benefits, with the costs associated with this occupational choice, including foregone earnings and investment costs for acquisition of skills required in that specific occupation. The worker will choose occupation j if and only if the discounted expected present value of future earnings in occupation j exceeds the discounted present value of future earnings in an alternative occupations k.

Under the assumption that each worker has a positive probability of selecting into an occupation j and that the choice of an occupation j is mutually excludable from the choice of occupation k, the probability of choosing occupation j can be described by a multinomial logit as:

$$Occup_{ig} = \gamma_{0g} + \gamma_{1g}NCS_{ig} + \gamma_{2g}X_{ig} + \gamma_{3g}Z_{ig} + u_{ig} \tag{2}$$

where $Occup_{ig}$ is an index value of each individual i of gender g working in one of the J occupations, NCS_{ig} is a vector of noncognitive traits that make the worker more qualified to enter into occupation j, X_{ig} includes the same variables as in (1) and u_{ig} is an i.i.d. error term with the extreme value distribution. Z_{ig} is a vector of instruments that affect occupational attainment but do not directly affect worker market productivity. I include in Z_{ig} region-specific changes in the proportion of women employed in each occupation j and the socioeconomic class of the father when the worker was 16 years old.

Equation (1) augmented with endogenous occupation is described by:

$$lnW_{ig} = \beta_{0g} + \beta_{1g}NCS_{ig} + \beta_{2g}X_{ig} + \beta_{3g}Occup_{ig} + \epsilon_{ig} \tag{3}$$

where $Occup_{ig}$ is a vector of occupation categories from model (2), ϵ_{ig} is an error term and all other variables are as defined in (1).

Because wages are observed only if the worker chooses an occupational sector and because workers who choose a particular occupation are endowed with characteristics that cause them to sort into that occupation, estimating separately the occupational choice and the wage determination equations will give biased estimates. To overcome this endogenous selection into occupations, I use maximum likelihood to jointly estimate the reduced form multinomial logit in (3) for each occupation with the gender-specific wage equations in

(2) via a switching regression model with endogenous covariates (Lee 1983).[1] By jointly modeling equations (2) and (3), I identify the *direct* effect of noncognitive traits on wages ($\hat{\beta}_{1g}$), that is, the effect of noncognitive traits that does not operate through the choice of occupational sectors. For specifications where the workers are observed for more than two time periods, I cluster the standard errors at the individual level.

The *indirect* effects of noncognitive traits on wages ($\beta_{3g}\gamma_{1g}$) are identified as the difference between the estimated coefficients under the total and the direct effects, and are given as $\delta_{1g} - \beta_{1g}$. This implies that I may underestimate the contribution of noncognitive traits on wages if I ignore their impact on occupational choice if, for example, workers sort into the lower-paying occupations because of these traits.

The estimated vector $\hat{\beta}_{1g}$ in (3) may also be biased if NCS_{ig} is endogenous; not only noncognitive skills increase worker productivity and wages, but noncognitive skills may also be influenced by the wages the worker receives or by the conditions in the working environment. To alleviate concerns of reverse causality, in the analysis I use pre-labor market measures of noncognitive traits. Therefore, my results should be interpreted as the effect of pre-labor market noncognitive traits on the gender wage gap.[2]

3.3 Decomposition of Gender Wage Differentials

Wage differences between men and women can be attributed, among others, to women being endowed with noncognitive traits that are not demanded in the labor market (*e.g.*, Bowles, Gintis and Osborne 2001). Given the occupational choice model, workers will try to match a multitude of noncognitive traits with their occupation. Hence, I need an empirical method that will allow me to separate the contribution of noncognitive traits from other determinants of male-female wage differences. Also, because some noncognitive traits are more productive in certain occupations than in others, and given evidence of female occupational sorting (*e.g.*, Bayard *et al.* 2003), heterogeneity of prices across occupations is important for understanding the determinants of the gender wage gap. Thus, the empirical method needs to further separately identify the contribution of returns

[1] One important implicit assumption of a MNL formulation is the independence of irrelevant alternatives. For every model, I tested the null hypothesis of IIA satisfaction using the method suggested by Small and Hsiao (1985) and, for each category included, I find support of the IIA. This is evidence that multinomial logit specifications are appropriate for my data.

[2] My choice to use pre-labor market measures of noncognitive skills follows standard practices that control for lagged noncognitive skills (*e.g.*, Borghans, ter Weel and Weinberg 2008; Heckman, Stixrud and Urzua 2006). There are no concerns of reverse causality for cognitive skills as there is consensus that they are determined by the age of 10. For noncognitive skills, the issue is not settled as there is evidence from the psychology literature that personality traits are relatively stable over the lifetime (*e.g.*, Almlund *et al.* 2011) and that they are malleable over the lifecycle responding to changing conditions over the lifecycle (*e.g.*, Srivastava *et al.* 2003).

to noncognitive traits to gender differences in wages. I employ the Oaxaca and Ransom (1994) wage decomposition because it both separates gender wage differentials into a portion due to differences in characteristics and a portion due to differences in returns to these characteristics, *and* it identifies the effect of each noncognitive skill separately (*i.e.*, conscientiousness versus agreeableness) on the gender wage gap.

The average wage difference between men and women can be decomposed as:

$$(\overline{lnW_m}) - (\overline{lnW_f}) = (\bar{X}_m - \bar{X}_f)\hat{\beta}_p + \bar{X}_m(\hat{\beta}_m - \hat{\beta}_p) + \bar{X}_f(\hat{\beta}_p - \hat{\beta}_f) \tag{4}$$

where $(\overline{lnW_m})$ and $(\overline{lnW_f})$ are the means of the log wages of men and women, X_m and X_f are the vectors of explanatory variables defined in (1), and $\hat{\beta}_p$ is a vector of estimated coefficients from a model where men and women are pooled together, with gender included as a separate regressor in X. The first term on the right hand side in (4) is the portion of the gender wage gap attributed to differences in characteristics of the workers (endowments component), while the last two terms represent differences due to differential returns (coefficients) associated with these characteristics. This decomposition method takes into account the weighted average of the gender groups instead of using only men or only women as the reference group, because employers are not interested in the gender of their potential employees per se but in the relative number of men and women they employ (Neumark 1988; Oaxaca and Ransom 1994).

The decomposition method in (4) when occupation is excluded from X_{ig} (based on equation (1)) captures the total contribution of noncognitive traits to the gender wage gap, while the decomposition when the endogenous selection into occupations is accounted for (based on equations (2) and (3)) identifies the direct effect. The indirect effect is calculated as the difference between the model for the total effect and the model for the direct effect of noncognitive traits on the gender wage gap.

Even though alternative methods have been proposed in the literature for decomposing the gender wage gap, they are not appropriate for my analysis because they do not assess the contribution of each skill measure separately on the wage gap (Fairlie 2005; Machado and Mata 2005; Melly 2005; see Fortin, Lemieux and Firpo 2011 for a review). Also, I do not employ a decomposition method across the wage distribution—despite that they can assess the contribution of each skill separately on gender wage differences (Firpo, Fortin and Lemieux 2007)—because the Oaxaca decomposition method facilitates more direct comparison with previous studies (*e.g.*, Cobb-Clark and Tan 2011; Fortin 2008; Mueller and Plug 2006).

4 Data

4.1 National Child Development Study Data

I use data from the National Child Development Study (NCDS), a longitudinal cohort study that follows all children born in March 3-9, 1958 in the United Kingdom. The NCDS is designed to monitor such key domains as cognitive and noncognitive skill formation, family background, health, education, and social and economic outcomes. Information on each participant has been collected eight times to date, at ages 7, 11, 16, 23, 33, 42, 46 and 50. When participants were ages 7 and 11 the information was reported by parents, teachers and school administrators; participants were first interviewed at age 16. Every member of the original sample (consisting on 18,558 children) was eligible to participate conditional on staying within the geographic regions of England, Wales and Scotland, regardless of whether they changed household.[3]

The NCDS is suitable for my paper because it includes both noncognitive skill measures and details on the occupational choice and wages of the same individuals as adults. By using noncognitive skill measured at age 16, I can address the issue of endogeneity of noncognitive skills. The longitudinal nature of the dataset also facilitates the comparison of my findings with the current literature; I can utilize information from different ages to replicate the results of other studies on role of noncognitive skills as determinants of the gender wage gap and then show how these results change once I account for the indirect effect of noncognitive skills due to selection into occupations based on these skills.

4.2 Sample Selection Criteria

Table 1 shows the number of respondents I dropped from the analysis with each selection criterion. I restrict my analysis to ages 33 and 50 because complete information is available on the three key variables (wages, occupation and noncognitive skill) at these ages. The target population to be interviewed was 15,558 at age 33 and 12,316 at age 50. Due to intractability, refusal to participate, non-availability or incomplete questionnaires of the participants, 11,460 and 9,790 respondents were interviewed at each respective age. I impose the following sample selection rules: First, I include only individuals who had information on their wages and hours of work to construct the hourly wages measure. I do not include self-employed workers because, relative to employees, they are less constrained by institutional rules with respect to length of work week, and they are better able to adjust the amount and type of labor supplied. I exclude workers in the armed forces because

[3] For more information on round 5 (age 33) see Dodgeon, Elliot, Johnson and Shepherd (2006) and on round 8 (age 50) see Brown, Elliot, Hancock, Shepherd and Dodgeon (2010).

they follow different career paths than non-military workers. Second, workers must have indicated their occupation. I further reduce the sample to workers who had complete information on the noncognitive skills questionnaire at age 16. However, for cognitive skill instead of eliminating workers who did not participate in the cognitive assessment tests at age 16, I impute missing values with their performance in these tests at age 11. After imposing these selection criteria to workers who were present in both age 33 and age 50, I end up with a sample of 7,600 individual-year observations.[4]

4.3 Variables

4.3.1 Dependent Variables

Table 2 presents summary statistics of all the variables included in the analysis. My dependent variable in the wage regressions and the decomposition of the gender wage gap is the logarithm of the price-adjusted average hourly wage. I construct a worker's hourly wage rate by dividing weekly labor earnings by hours worked during this time period and deflating it using the European Union's 2000 harmonized consumer price index.

For the occupational attainment model I use information on the worker's occupation in the current job. Because I examine two separate cross-sections, I need a uniform taxonomy for the occupation categories. I assign each worker to an occupation using the 2000 Standard Occupational Classification (the system used in the age 50 interviews), which can be directly mapped to the 1990 Standard Occupational Classification (the system used in the age 33 interviews). Given this classification system I create eleven occupational groups in order to have detailed occupation categories while maintaining a sufficient number of observations per category: managers; business, science and other professionals; health and education professionals; business, science and other associates; health associates; administrative; skilled trade; sales; personal services; operational occupations; and elementary occupations. I present details on the jobs included in each category in appendix Table A1.

4.3.2 Noncognitive and Cognitive Skills

The variable of primary interest in equations 1-4 is the vector of noncognitive skills. I measure noncognitive skills using maternal behavioral assessments of participants at age 16; the mothers report on a Likert-scale whether certain behaviors apply to their

[4] Replication of the analysis for a less restricted sample where a worker was included in the sample if he had participated in at least one round, resulting in a sample of 6,150 and 4,515 individuals aged 33 and 50 respectively, gave similar results as the ones presented in the following sections. However, because I examine why the role of noncognitive skills changed between the two ages, I choose the more uniform sample of workers who were present in both ages.

child, with higher values indicating a more prevalent behavior. The exploratory factor analysis showed that the questions capture five child behaviors;[5] the first trait captures the tendency towards intellectual curiosity and variety of experiences. The second trait refers to the ability to deal with problems, be well-organized and self-disciplined. The third trait focuses on the degree of social interactions, in particular, sociability, friendliness and gregariousness. The fourth trait also relates to interpersonal tendencies capturing the predisposition of getting along with others, avoiding conflicts and helping others. The firth trait is associated with experiencing strong positive and negative emotions (*i.e.*, anger, fear, nervousness). These five traits correspond to the Big Five taxonomy developed in the psychology literature (*e.g.*, Goldberg 1990)—openness to experience, conscientiousness, extraversion, agreeableness and neuroticism, respectively—and are accepted as a universal construct for measuring personality by researchers from different disciplines (*e.g.*, John and Srivastava 1999).

I use reading comprehension and mathematics test scores taken at age 16 to measure cognitive skills. Both tests were designed by the National Foundation for Educational Research in England and Wales (NFER) to measure accumulated cognitive skills throughout pre-schooling and schooling years. A higher score on either test means that the respondent has given more correct responses indicating a higher underlying cognitive skill. Because some participants have complete information on the noncognitive assessments, but have not participated in the cognitive assessments, instead of dropping observations with missing values in cognitive skills, I impute their missing values. That is, for the few cases with missing values in math or reading tests at age 16, I assign the score they achieved at age 11 in the math or reading test, and use indicators variables to identify these imputed cases.

Because cognitive and noncognitive skills are measured on different scales—the reading comprehension test ranges from 0 to 35, the math test ranges from 0 to 31, and the behavioral assessments have different ranges—I standardize skill-specific test scores to have mean zero and standard deviation of one for each participant. These standardized test scores show the effect of a one-standard deviation from the mean on the dependent variable (*i.e.*, wages or occupation).

[5] To determine the appropriate number of factors to retain in my analysis I use Kaiser's criterion of retaining as many factors as eigenvalues greater than the unity and include only the factor loadings whose values exceed 0.4 for the main factor and 0.25 for all the other factors. In addition to the exploratory factor analysis I also examined Cattell's Scree plot, Horn's Parallel Analysis and Velicer's Minimum Average Partial Correlation all of which were in favor of retained between 4 and 5 traits in the analysis. The validity of the five constructed measures is further corroborated by the Cronbach's alpha reliabilities test (Cronbach 1951).

4.3.3 Other Explanatory Variables

The vector X_{jt} controls for various demographic, household, regional, and labor market characteristics. I include self-assessed health status and a measure of depression to net out any psychiatric conditions from the domain of neuroticism. The former is a dummy variable coded one if the individual rates his health status as good or very good, while the latter is the Malaise Score which is based on twenty-four (age 33) or nine (age 50) questions. I expect that such health conditions, if any, will be more important at later ages and exert a negative impact on wages of either gender. The depression scale is standardized as above.

Other measures of human capital investments include education, potential and actual work experience. I use retrospective data on highest qualification completed at age 23 to create six educational dummies; no formal education, secondary education, O-level, A-level, technical/higher diploma and college degree.[6] Potential experience is measured as age net of years of schooling minus six. I construct actual experience using the Event History Questionnaire which includes information on the start and end periods of employment. I calculate the total months a worker was employed in each job, sum their experience from all jobs and transform them into years of actual experience. Both types of experience are in quadratic specifications to capture that on-the-job training investments decline over time (Mincer 1974).

I use dummy variables about the presence of dependent children in the household under the age of 14, and being married, while I also include a continuous, discrete, variable for household size to capture family responsibilities.[7] Race is a binary variable for white (versus non-white) included to capture cultural differences in the tendency to work.

To account for labor market characteristics, like differences in other input prices or real wages, I add several indicator variables on if the respondent works in the private sector, is member of a union, works under a temporary contract, has managerial duties in the current job, works full-time, has received on-the-job-training from the employer and works in a small, medium or large firm.[8,9] I proxy regional labor market differences through

[6] Secondary education refers to individuals who graduated from high school but did not take formal exams, while those who also took the national exams are classified in the O-level category. Those who sat for exams, but decided not to pursue further education after passing these exams are in the A-level group. Individuals with technical diplomas (*i.e.*, nurses or lawyers) are included in the higher diploma group and anyone with at least a college degree is part of the college category.

[7] Analysis using the number of children in the household gave similar results.

[8] If a worker supervises 3 or more workers is classified in the NCDS as having managerial duties. If the employer has paid for the worker to attend some vocational classes, the worker is said to have received on-the-job training. I define a firm as small if it occupies less than 25 employees, medium-sized if it has no more than 100 employees, and large if it employs more than 100 workers.[9] I define a full-time worker as working for 35 or more hours per week. However, I did not find significant

ten dummy variables for the region of residence based on the government office regions (GOR) classification: Northeast, Northwest, Yorkshire and Humber, East Midlands, West Midlands, East Anglia, Southeast (including the London metropolitan area), Southwest, Wales and Scotland.

4.3.4 Variables Used as Exclusion Restrictions

In the occupational attainment model (2), I include two measures as exclusion restrictions in the vector Z_{jt}. First, I use the socioeconomic group of the father when the respondent was age 16. Father's occupation classification is provided by the Registrar General to proxy preferences for occupation and exposure of the child to a given occupation. This social classification system is derived by mapping occupation and employment status to class categories taking into account the type of work performed by the fathers and their responsibilities within each occupation.[10] I create five socioeconomic class indicator variables that take the value one if the father was in a professional occupation, a managerial or technical occupation, a skilled occupation (both manual and non-manual), a partly-skilled occupation or an unskilled occupation. I also create a category for missing socioeconomic class for cases where the father was not present, the occupational classification was not valid or there was no response.

Second, I include the growth (or decline) in the proportion of women employed in each occupation. For each of the ten GORs I calculate the proportion of women relative to men that are employed in each of the eleven occupation groups defined in 4.3.1. After I adjust these female-to-male ratios with population weights to make them nationally representative, I calculate the change in employment from 1987 to 1990 and use it as an exclusion restriction for the age 33 analysis. For age 50 workers, I include in Z_{jt} the occupation-specific change in female-to-male employment from 2004 to 2007.[11]

Paternal socioeconomic class and gender-specific employment changes are valid exclu-

differences when I defined full-time employment as 30 or more hours per week.

[10] Fathers are assigned to social classes by a threefold process. First, according to the type of work and the nature of the operation performed each individual is assigned to an occupational group. Each occupational category is then assigned as a whole to a social class without taking into account any skill differences between individuals within the same occupation group. Finally, individuals with certain responsibilities within each occupational group—foreman or managers in particular—are reassigned to social classes that match better these responsibilities. For example, individuals of foreman status from social class IV or V are reallocated to social class III, and persons of managerial status are redistributed to social class II (OPCS, 1980).

[11] I draw information from the Labor Force Surveys which cover the whole U.K. Because I use information from three different decades, and because the occupational classification has changed over time, I match each occupation during the 1980s and 1990s with the SOC2000 using the 3-digit level. I also examined the change in gender-region-occupation-specific wages as potential exclusion variables using data from the General Household Survey for 1987-1990 and 2004-2007, but these wage measures did not satisfy the orthogonality condition.

sion restrictions for the multinomial logit model. For the occupational choice model, these restrictions are jointly significant at the 1% level based on a likelihood ratio (LR) test.[12] The Kleinbergen-Paap F-statistics are also above 10, which exceed the critical value of 5, suggesting that the instruments are jointly strong predictors of occupational attainment.[13] The orthogonality condition is also satisfied as the instruments are not predictive of wages for either gender. Tests of joint statistical significance of the exclusion restrictions in the gender-specific wage models led to non-rejection of the null hypothesis.[14] Therefore, I expect that paternal socioeconomic class and changes in the proportion of women employed in each occupation are valid instruments for occupation.

4.4 Summary Statistics

Table 2 shows that there is gender heterogeneity in noncognitive and cognitive skills. Men are more open to experiences (0.72), while women are generally more conscientious (2.48), extraverted (3.12) and agreeable (2.99). Men have also higher endowments of cognitive skills as they respond correctly to more questions in standardized math (15.4 vs. 13.4) and reading (26.9 vs. 26.4) tests. With the exception of neuroticism, men and women are statistically different at the 1% level consistent with the existing literature (see Almlund *et al.* 2011 for a review). These gender differences in skill endowments suggest that men and women may choose different occupations in order to match their noncognitive and cognitive skills.

Table 2 also shows that the gender wage gap has decreased between age 33 and age 50 (from 0.331 log points to 0.277 log points), even though men earn significantly more than women at both ages. The wage difference can be attributed to men having more human capital; four out of every ten men attain an upper level of education (A-Level, technical diplomas or college degrees) compared to three out of every ten women, they have more years of actual experience—approximately one extra year of working experience with the gender experience gap increasing from 1.1 years (age 33) to 1.5 years (age 50)—and work between 10 and 15 more hours per week than women. However, women have significantly

[12] The χ^2-statistic for age 33 men is 207.76, for age 50 men is 396.03, for age 33 women is 176.73 and for age 50 women is 567.91. In addition to the validity of the instruments, I examined if noncognitive skills are jointly significant in the occupational choice models. For age 33 men (78.38) and age 50 women (69.45) noncognitive skills jointly determine occupational choice at the 1% significance level, while for age 50 men and age 33 women they are jointly significant at the 10% level. For cognitive skills the respective χ^2-statistics were significant at the 1% level; 87.86 (age 33 men), 103.39 (age 50 men), 72.04 (age 33 women) and 52.84 (age 50 women).

[13] The Kleinberg-Paap F-statistic for age 33 men is 11.42, for age 50 men is 14.62, for age 33 women is 11.47 and for age 50 women is 14.64. I use this test only to get additional evidence for the validity of my instruments because a rigorous weak instrument test is not available for the multinomial case.

[14] The F-statistics are 1.68 for age 33 men, 1.91 for age 50 men, 1.50 for age 33 women and 1.13 for age 50 women.

increased their full-time participation in the market (from 42% to 62%), their labor market experience and their hours of work. These changes in the female characteristics along with their move to health, education and managerial occupations can account for the decline in the gender wage gap by 0.054 log points. In the next section I will show that the change in the occupational distribution and the increase in the full-time participation of women are the main explanations for the decrease in gender differences in wages between the two ages.

5 Results

5.1 Decomposition Results

My goal is to examine if endogenous selection into occupations changes our understanding about the contribution of noncognitive skills to the gender wage gap. I explore this question in Tables 3 and 4. The first set of estimates is obtained by estimating model (1) unconditional on occupation (total effect column). The next set of estimates comes from simultaneously estimating gender-specific wage and occupational attainment models (direct effect column). The third set of estimates is the difference between the previous two models (indirect effect column). Columns (1), (3), (5), (7), (9) and (11) report estimates to assess the portion of the gender wage gap that is explained by differences in worker characteristics, while columns (2), (4), (6), (8), (10) and (12) report estimates to assess the portion of the gender wage gap that is explained by differences in returns to these characteristics. Because the measurement scale of noncognitive and cognitive skills is different, the coefficients in Tables 3 and 4 show the effect of a one-standard deviation change in noncognitive and cognitive skills on the gender wage gap. Negatively signed coefficients represent traits that narrow the male-female wage differential. Positively signed coefficients mean that the examined skill contributes to widening the gender wage gap.

Table 3 includes the wage decomposition when I pool two observations per worker for ages 33 and 50. The gender wage gap of the logarithm of hourly wages amounts to 0.304 points. Column (1) shows that extraversion is the only noncognitive skill that exerts a significant effect on the gender wage gap. Women are more sociable than men (see Table 2) and their higher endowment in sociable skills contributes to narrowing the gender wage gap by 1.3(=0.004/0.304) percent of gender differences in wages. This contribution is much lower than the one of math skills, as differences in math explain 6.3% of the gender wage gap. The finding that noncognitive skills are less significant than other traditional skills like education or cognitive skills is shown in the bottom of the table. Noncognitive skills have a lower total contribution to the gender wage gap compared to both education and cognitive skills; less than 1% of the overall gender wage gap can be explained by differences in noncognitive skills' endowments between men and women, while 7.9% and 11.8% of the gap is due to differences in cognitive skills and education respectively. The finding that, noncognitive skills have a lower contribution to the gender wage gap—compared to cognitive skills and education—is consistent with previous studies that pool across years (*e.g.*, Braakman 2009).

By comparing the total and direct effects columns I demonstrate that endogenous selection into occupations understates the contribution of noncognitive skills to the gender wage gap. In column (3) we can see that differences in the endowments of conscientiousness, sociability and agreeableness are significant contributors to explaining wage differentials; 0.010 log points or 3.3% of the gender wage gap is due to women being more agreeable than men, while an additional 2.6% of the wage differential is attributed to conscientiousness and extraversion. Education (-0.136 or 44.7%) and cognitive skills (-0.085 or 28%) still have a higher magnitude of explaining gender wage differences, but now noncognitive skills account for a greater portion of the gender wage gap (-0.015 or 4.9%) compared to the case where indirect effects are ignored (0.002 or 0.7% under the total effects). This comparison shows that the contribution of noncognitive skills to the gender wage gap will be significantly underestimated if we do not account for endogenous selection into occupation.

Even though in Table 3 I verify that there are significant direct and indirect effects of noncognitive skills on the gender wage gap, these estimates may mask that worker heterogeneity varies across ages. I reject the null hypothesis of equal coefficients at ages 33 and 50 for noncognitive skills at the 5% significance levels, and the respective hypotheses for education and cognitive skills at the 1% significance levels. Because of these potential age varying effects, in Table 4 I report estimates separately for age 33 and age 50.

Columns (1)-(6) of Table 4 show the total, direct and indirect effects of interest for age 33 workers. Under the total effects, men earn significantly more than women because they are more endowed with cognitive skills and these skills, in turn, widen the gender wage gap. For example, an improvement in math performance by one standard deviation will increase the gender wage gap by 0.011 points. Noncognitive skills, on the other hand, do not have a significant contribution to the gender wage gap, as only extraversion can slightly decrease the gender wage gap by 1.5% (column (1)). However, noncognitive skills are important for the way men and women are allocated across occupations. Conscientiousness exerts a negative effect on the gender wage gap (-0.012 or 3.6% in column (3)). Since women are, on average, more conscientious compared to men (Table 2), they are endowed with a trait that makes them more productive in the market, thus, narrowing the gender wage gap. The same holds for agreeableness, decreasing the gender wage disparity by 13.6% (-0.045 in column (3)). Moreover, the total effect is higher than the direct effect for these two traits, which means that women are distributed across occupations in such a way that conscientiousness and agreeableness widen the gender wage gap: 0.013 and 0.046 in column (5), respectively. These results hold for extraversion as well. Therefore, women receive, on average, lower wages compared to men not because they are penalized for these noncognitive skills (non-statistically significant coefficients in column (6)), but because they choose occupations that do not require their higher endowment in conscientious, sociable or agreeable skills (positive and significant coefficients for conscientiousness, extraversion and agreeableness in column (5)).

The results for age 50 are given in columns (7)-(12) of Table 4. The findings for the total effects (columns (7) and (8)) are similar to the ones for age 33. With respect to the direct and indirect effects, conscientiousness and agreeableness are still the two noncognitive skills that have a statistically significant impact on the gender wage gap; the market offers a positive return to conscientious workers (0.044 in column (10)) and since women are more conscientious than men, 15.9% of the gap is attributed to differential returns for conscientiousness. The market also views agreeableness as a trait leading to a direct increase in productivity (-0.010 in column (9)) and this is reflected in the higher return to agreeableness given the way women are distributed across occupations (-0.047 in column (12)).

In terms of cognitive skills, despite men performing better in math tests (see Table 2), gender differences in math skills decrease the wage differential at age 33; an increase in math performance will decrease this differential by 0.027 points of a standard deviation (column (3)). This decrease indicates that because there is scarcity of women with high math ability in the market, women with higher endowment of math skills are perceived to be of higher productivity. However, women do not choose occupations based on their cognitive skills as the indirect effect shows that women choose occupations that widen the gender wage gap (0.038 in column (5)). The same holds for age 50. It is characteristic that the market regards math endowed women as more productive since differences in the endowment of math skills narrow the gender wage gap (-0.075 and -0.028 in column (9)), but women do not achieve a good matching between their cognitive skills and their occupation; the wage gap widens by 0.097 points and 0.025 points because of the way the workers are distributed across occupations given their math and reading skills (column (11)).

There are two important messages from the top part of Table 4. First, accounting for endogeneity of occupation is significant in order to assess the role of noncognitive skills on the gender wage gap similar to the findings in Table 3. In particular, the magnitude of the contribution of noncognitive skills to the gender wage gap is underestimated if we fail to account for endogenous selection into occupations—by 18 percentage points for age 33 and by 10 percentage points for age 50. The magnitude of this contribution is not negligible. As I show in the lower part of Table 4, the direct effect of noncognitive skills (19.9%) dominates the direct effect of cognitive skills (10.3%) and education (10.9%) at age 33. At age 50, there is a reversal with the direct effect of cognitive skills (34.7%) and education (30%) dominating the contribution of noncognitive skills (12.6%).

Second, in contrast to the pooled specification in Table 3, in Table 4 I show that are age differences with respect to the role of noncognitive skills on the gender wage gap. At early ages (age 33), differences in endowments in noncognitive skills (conscientiousness, extraversion, agreeableness) decrease the gender wage gap, which suggests that women *directly* benefit because of higher productivity in these skills. At mid-career ages (age 50), differences in returns to these endowments close the gender wage gap, suggesting that women *indirectly* benefit because they have sorted into occupations that reward their traits.

In order to better understand if occupational sorting is the explanation behind the decrease in the gender wage gap by 0.054 log points between the two ages, I also decomposed the decline in the gender wage gap between the two ages (not shown here). The results showed that changes in returns to noncognitive skills explain 22.4% of the decline in the wage differential, and an additional 24.1% (12.3%) of the decline is due to increases in the experience (full-time employment) of women. I do not find that the decline is due to changes in education or noncognitive skills because I treat both as predetermined traits. Hence, the decrease of the gender wage gap is partly attributed to the women being able to sort into occupations that reward them for their noncognitive traits, and to women increasing their attachment to the labor market since they have increased their hours of work participating, at age 50, as full-time workers.

5.2 Comparison with Previous Studies

Tables 3 and 4 showed that because workers choose their occupation based on their noncognitive skills, their total effects on the gender wage gap will be understated. In Tables 5 to 7, I replicate the analysis of three papers that investigate the relationship between noncognitive skills and gender wage gap to show that endogenous selection into occupations can explain why existing studies fail to find large effects of noncognitive skills on male-female wage differences.

In Table 5, I follow the empirical strategy by Mueller and Plug (MP) (2006) and focus on age 50 workers whose noncognitive traits are captured as post-market traits measured at age 50.[15] The MP results (column 1) show that differences in noncognitive skills (including differences in traits and differences in returns) explain only 2.7 (=0.016/0.587) percent of the gender wage gap.[16] Replication of their results for my sample gives similar results; column (2) shows that differences in noncognitive skills account for 3.2 (=0.009/0.277) percent of the gender wage gap, with agreeableness and neuroticism being the main traits that explain the gender wage gap. In column (3) I present the estimates from simultaneous estimation of models (2) and (3), and show that ignoring endogenous selection into occupations based on noncognitive skills downward biases the effect of noncognitive skills on the gender wage gap; 16.6 (=0.046/0.277) percent of the wage differential is due to noncognitive skills. This direct comparison between my study and MP clarifies that the small role of noncognitive skills in explaining gender differences in wages can be attributed to endogenous selection of workers in occupations in order to match their noncognitive skills.

In Table 6, I show that the underestimation of the contribution of noncognitive traits to the gender wage gap is valid for mid-career workers as well. I replicate the analysis by Fortin (2008) who investigates the impact of noncognitive skills on the gender wage gap for age 32 U.S. workers. Column (1) shows her results unconditional on occupation, which corresponds to the total effects of noncognitive skills on the gender wage gap (see Table 4B in her paper). The magnitude of the contribution of noncognitive skills when they are measured as standard measures of personality traits (*i.e.*, Big Five, locus of control, self-esteem) account for at most 14% of gender differences in wages.[17] In column (2) I report my estimates for the total effects of noncognitive skills on the gender wage gap where, instead of the Oaxaca-Ransom wage structure, I apply her pooled decomposition method where the advantage of men is equal to the disadvantage of women. Column (3) includes the direct effects of noncognitive skills on the gender wage gap under joint estimation of gender-specific wage and occupational choice models. Comparing columns (2) and (3) I find that ignoring workers' selection into occupations will downward bias the effect of interest; noncognitive skills explain 8.2 (=0.027/0.331) percent of the overall

[15] The only difference between Table 5 and Table 4 is that, in Table 5, noncognitive skills are measured simultaneously with wages and occupation. That is, in columns (2) and (3) I use post-labor market traits (age 50) instead of pre-labor market traits (age 16). The content of the post-labor market traits still captures the five aspects of a worker's personality, cognitive skills are still measured as pre-market test scores, and all other included variables are the same as in models (1) to (4). The wage decomposition method is based on the Oaxaca and Ransom (1994) method.

[16] See Table 6, rows (4) and (5) in MP.

[17] This contributions is higher when preferences over work and family are included as measures of noncognitive skills accounting for 22% of the gender wage gap.

gender wage disparity under endogenous treatment of occupation compared to just 1.5 (=0.005/0.331) percent unconditional on occupation.[18] This implies that the 14% of the variance of the gender wage gap explained by suuch traits might have been much higher if Fortin controlled for indirect effects of noncognitive skills operating through occupational choice.

In Table 7, I show that endogenous selection into occupations along with omitted cognitive skills bias is also a valid explanation for such an underestimation. Column (1) shows the results from Cobb-Clark and Tan (CCT) (2011) who conclude that noncognitive skills do not provide an explanation for the gender wage gap in Australia (see their Table 4B). In column (2) I replicate their methodology using a pooled sample of age 33 and age 50 workers when noncognitive skills are measured as pre-labor market traits and the gender wage gap is decomposed to explained and unexplained components using the Brown, Moon and Zoloth (1980) method. Column (2) corroborates their finding that the vast majority of the gender wage gap stems from disparity in wages between men and women who are employed in the same occupation (82.57%). More importantly, I show that the contribution of noncognitive skills to the gender wage gap is small and statistically insignificant (-0.004) similar to the CCT findings. However, the lack of significant contribution to the gap can be attributed to omission of cognitive skills from the analysis. In column (3) I show that inclusion of math and reading tests increases the importance of noncognitive skills to the gap. When I do not control for occupation the contribution of noncognitive skills to the gender wage gap is underreported (1.3%) compared to the case when cognitive skills are also available (10.2%). Thus, the negligible impact of noncognitive skills on the gender wage gap found in CCT may reflect omitted cognitive skills bias.

Moreover, the discrepancy between the two studies may also stem from CCT's choice of a decomposition method that does not treat occupation as endogenous and ignores the changing importance of noncognitive skills overtime. In Tables 3 and 4 I showed that there are both direct and indirect effects of noncognitive skills on the gender wage gap. My pooled sample analysis in Table 3 showed that under endogenous selection into occupation noncognitive skills can explain 4.9% of the gender wage gap. However, their effect on the wage gap is even higher when I separate my analysis by age; noncognitive skills can explain 19.9% (=0.066/0.330) of the wage disparity at age 33 and 12.6% (=0.035/0.277) at age 50. Therefore, CCT's results may also mask that the magnitude of the noncognitive skills' contribution to the gap varies by age groups.

[18] The 8.2% of the overall gap is the summed contribution of both the endowment and the coefficients component of noncognitive skills.

Hence, indirect effects of noncognitive skills are significant and should not be overlooked. This corroborates the finding in Borghans, ter Weel and Weinberg (2008) that the moderate role of noncognitive skills documented in the literature stems from failure to account for job assignment.

6 Concluding Remarks

In this paper, I disentangle the total, direct and indirect effects of noncognitive skills on the gender wage gap. The rationale is that noncognitive skills represent traits that affect productivity directly *and* shape workers' preferences over occupational choice. To identify these effects I simultaneously estimate gender-specific wage and occupational attainment models and, then, based on the method proposed by Oaxaca and Ransom (1994), I decompose the wage differential to find the contribution of each noncognitive skill to the gender wage gap. Using information from the National Child Development Study for two distinct ages (33 and 50) and controlling for pre-labor market noncognitive and cognitive skills, I report that noncognitive skills are significant contributors to the gender wage gap for British workers. This is in accordance with previous studies claiming that the small role of noncognitive skills on male-female wage differences may stem from failure to account for the effect of noncognitive skills on job assignment (Borghans, ter Weel and Weinberg 2008). It is also in contrast to studies reporting a small effect of noncognitive skills on the gender wage gap (Mueller and Plug 2006) and studies finding that noncognitive skills do not explain the gender wage gap (Cobb-Clark and Tan 2011).

By accounting for the role of noncognitive skills on occupational choice and allowing noncognitive skills to have heterogeneous effects for different ages, I contribute to the literature on the determinants of gender wage differentials. For the former, I show that the magnitude of the contribution of noncognitive skills to explaining wage differentials is underestimated by 18.4 percentage points for mid-adulthood and by 10.1 percentage points for late-adulthood when noncognitive skills' indirect effects on wages are ignored. For the latter, I demonstrate that in spite of noncognitive skills explaining gender differentials in both stages of the career, at age 33, the gender wage gap is driven by gender differences in endowments; women receive, on average, lower wages compared to men due to not choosing occupations that require their conscientious, sociable and agreeable traits, and not because they are penalized for these skills. At age 50, the wage differential is mainly due to differential returns to these traits; women are able to avoid occupations that penalize them for their personality traits and choose occupations that actually reward them for these traits. I also find that omission of cognitive skills from studies on the role of noncognitive skills can also explain their moderate effect on the gender wage gap.

One limitation of my study is that the choice of women to participate in the labor market is closely related to their noncognitive skills. Because certain noncognitive skills affect the propensity of women to enter the marriage market and constrain their participation in the labor market, the effect of such traits may be biased. For example, it is possible that more agreeable women choose marriage, childbearing and/or child-rearing over their career. If the more antagonistic women enter the labor market and the more agreeable women enter the marriage market, then the impact of agreeableness on wages and the gender wage gap will be overstated. Thus, it would be worthwhile to investigate how women with certain traits weight their decisions between entering the labor market and the marriage market.

Finally, since there is evidence that women choose occupations so as to match their noncognitive skills, an interesting extension would be to examine the relationship between employers' hiring practices and noncognitive skills. If the claim that employers have a preference over employees who match their own personality, or that employers prefer hiring workers with certain personality traits is valid, then an experiment could explore this issue. The idea would be to sequentially reveal more information to the employers about characteristics of their future employees, and observe how the wage offers change. Future work could investigate if the employers are affected in their hiring offers by cognitive skills, personality traits and gender of the potential employees, and whether there are any traits that are valued more by the employers.

7 References

Acemoglu, Daron, and David H. Autor. 2011. "Skills, Tasks and Technologies: Implications for Employment and Earnings." In *Handbook of Labor Economics* Volume 4B. eds. Orley Ashenfelter and David E. Card. Amsterdam: Elsevier.

Almlund, Mathilde, Angela L. Duckworth, James J. Heckman, and Tim Kautz. 2011, "Personality Psychology and Economics." In *Handbook of The Economics of Education* Volume 4. eds. Eric A. Hanushek, Stephen Machin and Ludger Woessmann. 1-181. Amsterdam: Elsevier.

Andrisani, Paul J. 1977. "Internal-External Attitudes, Personal Initiative, and the Labor Market Experience of White and Black Men." *Journal of Human Resources* 12(3):308-328.

Bayard, Kimberly, Judith Hellerstein, David Neumark, and K. Troske. 2003. "New Evidence on Sex Segregation and Sex Differences in Wages from Matched Employee-Employer Data." *Journal of Labor Economics* 21(4):887-922.

Borghans, Lex, Angela L. Duckworth, James J. Heckman, and Bas ter Weel. 2008. "The Economics and Psychology of Personality Traits." *Journal of Human Resources* 43(4):972-1059.

Borghans, Lex, Bas ter Weel, and Bruce Weinberg. 2008. "Interpersonal Styles and Labor Market Outcomes." *Journal of Human Resources* 43(4):815-858.

Bowles, Samuel, Herbert Gintis, and Melissa Osborne. 2001. "The Determinants of Earnings: A Behavioral Approach." *Journal of Economic Literature* 39(4):1137-1176.

Braakmann, Nils. 2009. "Psychological Traits and the Gender Gap in Full-Time Employment and Wages: Evidence from Germany." *Working Paper Series in Economics 112*. University of Lneburg. Institute of Economics.

Brown, Matt, Jane Elliot, Margaret Hancock, Peter Shepherd, and Brian Dodgeon. 2010. "National Child Development Study 2008-2009 Follow-Up (First Deposit): A Guide to the Dataset." *Centre for Longitudinal Studies*, www.cls.ioe.ac.uk/shared/get-file.ashx? itemtype =documentid=906.

Brunello, Giorgio, and Martin Schlotter. 2011. "Noncognitive Skills and Personality Tratis: Labour Marker Relevance and their Development in Education and Training Systems." *IZA Discussion Papers 5743*. Institute for the Study of Labor (IZA).

Cattan, Sarah 2012. "The Role of Workers' Traits in Explaining the Early Career Gender Wage Gap." *Job Market Paper*. University of Chicago.

Cobb-Clark, Deborah A., and Michelle Tan. 2011. "Noncognitive Skills, Occupational Attainment and Relative Wages." *Labour Economics* 18(1):1-13.

Dodgeon, Brian, Jane Elliot, Jon Johnson, and Peter Shepherd. 2006. "National Child Development Study: User Guide 2006." *Centre for Longitudinal Studies*, www.cls.ioe.ac.uk /shared/get-file.ashx?id=491itemtype=document.

Filer, Randall K. 1986. "The Role of Personality and Tastes in Determining Occupational Structure." *Industrial and Labor Relations Review* 39(3):412-424.

Fortin, Nicole M. 2008. "The Gender Wage Gap among Young Adults in the United States: The Importance of Money vs. People." *Journal of Human Resources* 43(4):884-918.

Fortin, Nicole, Thomas Lemieux, and Sergio Firpo. 2011. "Decomposition Methods in Economics." In *Handbook of Labor Economics* Volume 4A. eds. Orley Ashenfelter and David Card. 1-102. Amsterdam: Elsevier.

Goldberg, Lewis R. 1990. "An Alternative Description of Personality: The Big Five Factor Structure." *Journal of Personality and Social Psychology* 59(6):1216-1229.

Heckman, James J., Jora Stixrud, and Sergio Urzua. 2006. "The Effects of Cognitive and Noncognitive Abilities on Labor Market Outcomes and Social Behavior." *Journal of Labor Economics* 24(3):411-482.

Jackson, Michelle. 2006. "Personality Traits and Occupational Attainment." *European Sociological Review* 22(2):187-199.

John, Oliver P., and Sanjay Srivastava. 1999. "The Big Five Trait Taxonomy: History, Measurement, and Theoretical Perspectives." In *Handbook of Personality: Theory and Research* eds. L.A. Pervin and O.P. John. 102-138. New York: Guilford Press.

Keane, Michael P., and Kenneth I. Wolpin. 1997. "The Career Decisions of Young Men." *Journal of Political Economy* 105:473-522.

Krueger, Alan B., and David A. Schkade. 2008. "Sorting in the Labor Market: Do Gregarious Workers Flock to Interactive Jobs?" *Journal of Human Resources* 43(4):859-883.

Kuhn, Peter, and Catherine Weinberger. 2005. "Leadership Skills and Wages." *Journal of Labor Economics* 23(3):395-436.

Lee, Lung-Fei. 1983. "Generalized Econometric Models with Selectivity." *Econometrica* 51:507-512.

Light, Audrey, and Manuelita Ureta. 1995. "Early-Career Work Experience and Gender Wage Differentials." *Journal of Labor Economics* 13(1):121-154.

Mincer, Jacob. 1974. *Schooling, Experience and Earnings.* Columbia University Press: New York.

Mueller, Gerrit, and Eric S. Plug. 2006. "Estimating the Effect of Personality on Male-Female Earnings." *Industrial and Labor Relations Review* 60:3-22.

Nyhus, Ellen K., and Empar Pons. 2012. "Personality and the Gender Wage Gap."

Applied Economics 44(1):105-118.

Oaxaca, Ronald L. 1973. "Male-Female Wage Differentials in Urban Labor Markets." *International Economic Review* 14:693-709.

Oaxaca, Ronald L., and Michael R. Ransom. 1994. "On Discrimination and the Decomposition of Wages." *Journal of Econometrics* 61(1):5-21.

Office of National Statistics UK. 2011. http://www.statistics.gov.uk/methods_quality /soc/section1.asp.

Semykina, Anastasia, and Susan J. Linz. 2007. "Gender Differences in Personality and Earnings: Evidence from Russia." *Journal of Economic Psychology* 28(3):387-410.

Srivastava, Sanjay, Oliver P. John, Samuel D. Gosling, and Jeff Potter. 2003. "Development of Personality in Early and Middle Adulthood: Set Like Plaster or Persistent Change?" *Journal of Personality and Social Psychology* 84(5):1041-1053.

University of London. Institute of Education. Centre for Longitudinal Studies, National Child Development Study: Childhood Data, Sweeps 0-3, 1958-1974 [computer file]. 2nd Edition. National Birthday Trust Fund, National Children's Bureau, [original data producer(s)]. Colchester, Essex: UK Data Archive [distributor], August 2008. SN: 5565, http://dx.doi.org/10.5255/UKDA-SN-5565-1.

University of London. Institute of Education. Centre for Longitudinal Studies, National Child Development Study: Sweep 4, 1981, and Public Examination Results, 1978 [computer file]. 2nd Edition. National Children's Bureau, [original data producer(s)]. Colchester, Essex: UK Data Archive [distributor], August 2008. SN: 5566, http:// dx.doi.org/10.5255/UKDA-SN-5566-1.

University of London. Institute of Education. Centre for Longitudinal Studies, National Child Development Study: Sweep 5, 1991 [computer file]. 2nd Edition. City University. Social Statistics Research Unit, [original data producer(s)]. Colchester, Essex: UK Data Archive distributor], August 2008. SN: 5567, http://dx.doi.org/10.5255/UKDA-SN-5567-1.

University of London. Institute of Education. Centre for Longitudinal Studies, National Child Development Study: Sweep 8, 2008-2009: First Deposit [computer file]. 2nd Edition. Colchester, Essex: UK Data Archive [distributor], March 2010. SN: 6137, http://dx.doi.org /10.5255/UKDA-SN-6137-1.

Acknowledgments: I am grateful to the Centre for Longitudinal Studies (CLS), Institute of Education for the use of the National Child Development Study data and to the Economic and Social Data Service (ESDS) for making them available. However, neither CLS nor ESDS bear any responsibility for the analysis or interpretation of these data.

Table 1—Sample Selection Criteria

Age 33		Age 50		
No. of Individuals	% of Original Sample	No. of Individuals	% of Original Sample	Reason for Elimination
18,558		18,558		Total Cohort Members
				Ineligible due to:
-2,171	-17.9%	-1,252	-6.7%	Permanent refused or missing address
-41	0.2%	1,355	7.3%	Death
-517	-2.8%	1,240	-6.7%	Emigration
-59	-1.4%	-2,310	-12.4%	Untraced (including armed forces)
-480	-2.6%	-85	-0.5%	Refused
15,290	**82.4%**	**12,316**	**66.4%**	**Eligible Sample**
				Missing due to:
-1,718	-9.3%	-855	-4.6%	Non-tractable
-257	-1.4%	-125	-0.7%	Non-confirmation of address
-1,822	-9.8%	-1,214	-6.5%	Refusal in current round
-33	-0.2%	-332	-1.8%	Other unproductive (*i.e.*, ill, lost data, away during fieldwork period, etc)
11,460	**61.8%**	**9,790**	**52.8%**	**Completed Interviews**
				Elimination due to:
-2,244	-12.1%	-2,885	-15.5%	Not in the labor force, unemployed, self-employed or in the armed forces
-389	-2.1%	-376	-2.0%	Missing wages or occupation
-1,210	-6.2%	-920	-5.0%	Non-interview at age 23
-1,451	-7.8%	-1,085	-5.8%	Non-response in noncognitive skills questions at age 16
-16	-0.1%	-9	-0.0%	Non-response in cognitive skills in age 11 or age 16
-2,320	-12.5%	-685	-3.7%	Presence in both age 33 and age 50
3,830	**20.6%**	**3,830**	**20.6%**	**Final Sample**

Source: National Child Development Study

Table 2—Means and Standard Deviations of Dependent and Explanatory Variables, by Gender and Age

	Age 33					Age 50				
	Men		Women			Men		Women		
	Mean	S.D.	Mean	S.D.	Gender Difference[a]	Mean	S.D.	Mean	S.D.	Gender Difference[a]
	[1]	[2]	[3]	[4]	[1]-[3]	[5]	[6]	[7]	[8]	[5]-[8]
Natural Logarithm of Hourly Wage	1.91	(.49)	1.58	(.51)	.33**	2.24	(.56)	1.96	(.49)	
Noncognitive Skills										
Openness to experience	.72	(.33)	.64	(.39)	.08**	.72	(.33)	.64	(.39)	.08**
Conscientiousness	2.39	(.63)	2.48	(.63)	-.09**	2.39	(.63)	2.48	(.63)	-.09**
Extraversion	3.00	(.56)	3.12	(.51)	-.12**	3.00	(.56)	3.12	(.51)	-.12**
Agreeableness	2.97	(.22)	2.99	(.21)	-.03**	2.97	(.22)	2.99	(.21)	-.03**
Neuroticism	1.33	(.38)	1.31	(.39)	.01	1.33	(.38)	1.31	(.39)	.01
Cognitive Skills										
Math	15.35	(7.23)	13.39	(6.73)	1.97**	15.35	(7.23)	13.39	(6.73)	1.97**
Reading	26.93	(6.52)	26.41	(5.99)	.51*	26.93	(6.52)	26.41	(5.99)	.51*
Education										
1 if no formal education[b]	.15		.20		-.05**	.15		.20		-.05**
1 if secondary education	.04		.03		-.01	.04		.03		-.01
1 if O-level	.25		.36		-.11**	.25		.36		-.11**
1 if A-level	.22		.11		.11**	.22		.11		.11**
1 if technical/higher diploma	.09		.11		-.02+	.09		.11		-.02+
1 if college degree	.13		.10		.03**	.13		.10		.03**
1 if missing education	.12		.09		.03*	.12		.09		.03*
Demographics										
1 if married	.69		.73		-.04*	.74		.70		.04**
1 if presence of children	.63		.74		-.11**	.85		.84		.01
1 if white	.98		.98		.00	.98		.98		.00
1 if good health	.90		.90		.00	.59		.58		.01
Household size	3.31	(3.46)	3.39	(1.35)	-.08	3.00	(1.24)	2.87	(1.10)	.13**
Depression scale/malaise	46.34	(2.31)	45.52	(2.82)	-.82**	.95	(1.44)	1.60	(1.92)	-.65**
Region										
1 if Northeast	.07		.06		.01	.07		.06		.01
1 if Northwest	.10		.11		-.01	.10		.11		-.01
1 if Yorkshire-Humber	.09		.09		.00	.09		.09		.00
1 if East Midlands	.08		.06		.02*	.08		.06		.02+
1 if West Midlands	.09		.09		.00	.08		.09		-.01
1 if East of Anglia[b]	.04		.04		.00	.05		.04		.01
1 if Southeast	.29		.29		.00	.26		.27		-.01
1 if Southwest	.08		.09		-.01*	.09		.10		-.01
1 if Wales	.06		.05		.01	.06		.05		.01
1 if Scotland	.11		.11		.00	.11		.11		.00
Job Characteristics										
Cumulative experience	10.14	(3.09)	10.17	(2.76)	-.04	25.93	(3.30)	26.16	(2.88)	-.23*
Actual experience	5.10	(4.62)	3.98	(4.11)	1.12**	14.81	(6.93)	13.31	(8.43)	1.49**
Weekly hours of work	43.95	(9.65)	28.83	(12.76)	15.11**	44.84	(9.41)	34.13	(11.88)	10.71**

(continued)

Table 2—(continued)

1 if on-the-job training	.64		.49		.16**	.51		.55		-.04*
1 if fulltime employment	.95		.42		.53**	.98		.62		.36**
1 if private sector	.65		.53		.12**	.70		.47		.23**
1 if union member	.45		.32		.13**	.35		.27		.08**
1 if managerial duties	.60		.42		.18**	.55		.40		.15**
1 if temporary contract	.04		.09		-.05**	.03		.04		-.01
Firm Size										
1 if small firm[b]	.24		.39		-.15*	.27		.35		-.08**
1 if medium firm	.26		.24		.02	.23		.26		-.03*
1 if large firm	.50		.37		.13**	.50		.39		.11**
Instrumental Variables										
Father's socioeconomic class at age 16:										
Non-skilled[b]	.06		.05		.01	.06		.05		.01
Semiskilled	.21		.14		.07	.21		.14		.07
Skilled	.49		.50		-.01	.49		.50		-.01
Managerial	.14		.20		-.06	.14		.20		-.06
Professional	.04		.06		-.02	.04		.06		-.02
Missing	.05		.06		-.01	.05		.06		-.01
Change in employment between 1987 and 1991	-.35	(1.82)	.10	(1.04)	-.45**					
Change in employment between 2004 and 2007						-.17	(.73)	-.18	(.98)	.01
Occupation										
Elementary	.06		.07		-.01	.07		.07		.00
Operational	.11		.04		.07**	.11		.02		.09**
Sales	.04		.10		-.06**	.02		.08		-.06**
Personal Service	.07		.14		-.07**	.02		.14		-.12**
Skilled Workers	.20		.02		.18**	.16		.01		.15**
Administration	.07		.29		-.22**	.06		.24		-.18**
Health Associates	.01		.08		-.07**	.01		.11		-.10**
Business & Other Associates	.09		.05		.04**	.14		.06		.08**
Education & Health Professions	.05		.08		-.03**	.06		.11		-.05**
Other Professionals	.08		.03		.05**	.08		.03		.05**
Managers[b]	.21		.10		.11**	.27		.12		.15**
Sample Size	1,780		2,050			1,780		2,050		

[a]Difference between men and women in mean characteristics.
[b]Reference groups for the indicator variables included in the analysis.
+ p<.10, * p<.05, ** p<.01. P-value is for test of equality in mean characteristics by gender.

Table 3—Estimated Effects of Noncognitive Skills on the Gender Wage Gap for both ages 33 and 50

	Total Effect		Direct Effect		Indirect Effect	
	[1]	[2]	[3]	[4]	[5]	[6]
Logarithm of Gender Wage Gap	.304**		.304**		.304**	
	(.012)		(.012)		(.012)	
Openness	.001	-.001**	-.002	.002**	.003*	-.003
	(.002)	(.001)	(.001)	(.001)	(.001)	(.002)
Conscientiousness	.002	-.001*	-.008**	.005**	.010**	-.006+
	(.001)	(.000)	(.002)	(.001)	(.002)	(.003)
Extraversion	-.004**	-.001**	.008**	-.006**	-.012	.005**
	(.001)	(.000)	(.003)	(.001)	(.005)	(.002)
Agreeableness	-.000	-.000	-.010**	.004**	.010**	-.004
	(.001)	(.000)	(.002)	(.001)	(.001)	(.001)
Neuroticism	.001	.000	.002	-.001	-.001	.001
	(.001)	(.000)	(.001)	(.001)	(.001)	(.000)
Math	.019**	-.002**	-.050**	.016**	.069*	-.018**
	(.003)	(.001)	(.009)	(.004)	(.005)	(.003)
Reading	.003**	.000	-.017**	.003+	.020*	-.003
	(.001)	(.000)	(.005)	(.002)	(.001)	(.002)
Difference in GWG due to:						
Cognitive skills	.024**		-.085**		.109**	
Noncognitive skills	.002		-.015*		.017*	
Education	.036**		-.136**		.172**	

+ p<.10, * p<.05, ** p<.01.

Notes: Sample consists of 7,660 observations; two observations per 3,830 workers who participated in both ages 33 and age 50. Bootstrapped standard errors with 100 replications are reported in parenthesis clustered for person-year observations.

Columns [1], [3] and [5] show the proportion of the gender wage gap that is explained by differences in the characteristics of men and women. Columns [2], [4] and [6] show the proportion of the gender wage gap that is explained by differences in the returns to these characteristics.

Table 4—Estimated Effects of Noncognitive Skills on the Gender Wage Gap, Decomposition Results by Age

	Age 33						Age 50					
	Total Effects		Direct Effects		Indirect Effects		Total Effects		Direct Effects		Indirect Effects	
	[1]	[2]	[3]	[4]	[5]	[6]	[7]	[8]	[9]	[10]	[11]	[12]
Logarithm of Gender Wage Gap	.331**		.331**		.331**		.277**		.277**		.277**	
Openness	.000	-.002*	-.004	.002	.004	-.004	.000	.003	.017*	.003	-.017	.000
	(.001)	(.003)	(.004)	(.002)	(.005)	(.009)	(.002)	(.003)	(.007)	(.009)	(.000)	(.007)
Conscientiousness	.001	-.001+	-.012*	.014*	.013**	-.015	.003	.001	-.026*	.044**	.029	-.043**
	(.001)	(.006)	(.006)	(.007)	(.003)	(.012)	(.002)	(.007)	(.012)	(.016)	(.017)	(.005)
Extraversion	-.004**	-.001+	-.006*	.007	.002	-.008	-.003	.000	.009	-.012	-.012	.012
	(.002)	(.004)	(.005)	(.005)	(.004)	(.006)	(.003)	(.004)	(.006)	(.011)	(.016)	(.008)
Agreeableness	.001	-.000	-.045**	-.024**	.046**	.024	-.001	-.008	-.010*	.039*	.009	-.047**
	(.001)	(.006)	(.013)	(.009)	(.003)	(.017)	(.001)	(.007)	(.005)	(.017)	(.018)	(.003)
Neuroticism	-.000	.000	.006	-.004	-.006	.004	.001	-.002	.009	-.038	-.008	.036
	(.001)	(.007)	(.006)	(.007)	(.009)	(.009)	(.001)	(.008)	(.007)	(.042)	(.007)	(.047)
Math	.011**	-.001	-.027+	-.002	.038**	.001	.022**	-.002	-.075**	.001	.097**	-.003
	(.003)	(.005)	(.015)	(.008)	(.018)	(.009)	(.005)	(.007)	(.026)	(.013)	(.031)	(.007)
Reading	.003*	.000	.001+	-.006	.002**	.006	.004*	-.008	-.025*	-.003	.029*	-.005
	(.001)	(.006)	(.001)	(.005)	(.001)	(.011)	(.002)	(.007)	(.012)	(.003)	(.016)	(.008)
Total difference in GWG due to:												
Cognitive Skills	.013**		-.034**		.047**		.016*		-.096**		.112**	
Noncognitive Skills	-.005		-.066**		.061**		-.007		.035**		-.042**	
Education	.030**		.036**		-.006+		.037**		-.083**		.120**	
Experience	.053**		.043**		.010+		.043**		-.025**		.068*	

+ p<.10, * p<.05, ** p<.01.

Notes: For each age the sample consists of 2,050 female workers and 1,780 male workers. Bootstrapped standard errors with 100 replications are reported in parenthesis.

Columns [1], [3], [5], [7], [9] and [11] show the proportion of the gender wage gap that is attributed to differences in the endowments of men and women. Columns [2], [4], [6], [8], [10] and [12] show the proportion of the gender wage gap that is explained by differences in the returns to the characteristics of men and women.

Table 5—Comparison of Main Results on the Effects of Noncognitive Skills on the Gender Wage Gap with Mueller and Plug (2006)

	[1] Mueller and Plug[a]- Exogenous Occupation	[2] Current Paper - Exogenous Occupation	[3] Current Paper - Endogenous Occupation
Log Gender Wage Gap	.587	.277	.277
Difference in GWG due to characteristics			
Openness	-.001	.003*	.001
Conscientiousness	-.001	.001	-.005
Extraversion	-.000	-.001	.017+
Agreeableness	.035	.030**	.025
Neuroticism	.011	.008*	.016*
Difference in GWG due to coefficients			
Openness	-.002	-.001	-.000
Conscientiousness	.000	.001	.003
Extraversion	.000	.000	.008+
Agreeableness	-.017	-.027**	-.014
Neuroticism	-.008	-.005*	-.004
Total difference in GWG due to[b]			
Noncognitive Skills	.016	.009**	.046**
Cognitive Skills	-	.017**	-.003
Sample Size	5,025	3,830	3,830

+ p<.10, * p<.05, ** p<.01.

[a]Level of statistical significance is not available for the Mueller and Plug paper.

[b]The total difference sums the differences due to both the characteristics component and the coefficients component.

Notes: Robust standard errors are in parenthesis. In all three columns workers are at age 50; wages, occupation and noncognitive skills are measured concomitantly at the post-market age 50; the wage decomposition is based on the Oaxaca and Ransom (1994) method. For columns (1) and (2) occupation is exogenous and for column (3) occupation is endogenous.

Table 6—Comparison of Main Results on the Effects of Noncognitive Skills on the Gender Wage Gap with Fortin (2008)

	[1]	[2]	[3]
	Fortin - No Occupation	Current Paper - No Occupation	Current Paper - Endogenous Occupation
Log Gender Wage Gap	22.94	.331	.331
Difference in GWG due to characteristics			
Noncognitive Skills	1.92	-.005+	.049**
	(0.41)	(.003)	(.012)
Cognitive Skills	0.35	.013**	-.025+
	(0.25)	(.003)	(.013)
Difference in GWG due to coefficients			
Noncognitive Skills	3.14	-.000	-.022
	NA	(.001)	(.016)
Cognitive Skills	NA	.001	.007
	NA	(.001)	(.011)
Total difference in GWG due to[b]			
Noncognitive Skills	5.06	-.005	.027**
Cognitive Skills	NA	.014	-.018+
Sample Size	6,522	3,830	3,830

+ p<.10, * p<.05, ** p<.01.

[b]The total difference sums the differences due to both the characteristics component and the coefficients component.

Notes: Standard errors are in parenthesis. NA means not available. In all three columns workers are at age 32-33; wages and occupation are measured at age 33 while cognitive and noncognitive skills are measured as pre-market traits; the wage decomposition is based on the Fortin wage decomposition method. For columns (1) and (2) occupation is not included in the vector of explanatory variables *X* and in column (3) occupation is endogenous using the switching regression model presented in section 3.

Table 7—Comparison of Main Results on the Effects of Noncognitive Skills on the Gender Wage Gap with Cobb-Clark and Tan (2011)

	[1]		[2]		[3]	
	Cobb-Clark & Tan - Unconditional on Cognitive Skills		Current Paper - Unconditional on Cognitive Skills		Current Paper - Conditional on Cognitive Skills	
	Wage Gap	%	Wage Gap	%	Wage Gap	%
Log Gender Wage Gap	.143		.304		.304	
Intra-Occupational						
Explained Component	.031		.117		.224	
Unexplained Component	.107		.134		.030	
Total Intra-Occupational Gap	.138	96.59%	.251	82.57%	.254	85.50%
Inter-Occupational						
Explained Component	-.001		.016		.019	
Unexplained Component	.005		.037		.023	
Total Inter-Occupational Gap	.005	3.41%	.053	17.43%	.043	14.50%
Total difference in GWG due to						
Noncognitive Skills	NA		-.004	1.32%	-.031	10.20%
Cognitive Skills	NA		-		.096	31.58%
Sample Size	21,106		7,600		7,600	

+ p<.10, * p<.05, ** p<.01.

Notes: Standard errors are in parenthesis. The specifications focus on pooled samples for the first six waves of the HILDA (column (1)) and or the ages of 33 and age 50 for the NCDS (columns (2) and (3)). Cognitive skills and noncognitive skills are measured as pre-labor market traits and the wage decomposition is based on the Brown, Moon and Zoloth (1980) method. Column (1) includes estimates of Cobb-Clark and Tan (2011) using the Household Income and Labor Dynamics in Australia (HILDA) unconditional in cognitive skills, column (2) includes my estimates for the NCDS sample unconditional on cognitive skills and column (3) includes my estimates for the NCDS sample conditional on both noncognitive and cognitive skills.

Table A1—Occupational Categories based on the Standard Occupational Classification 2000

Major Group	Occupation Category	Minor Group	3-Digit Occupation Title
1	Managers and Senior Officials	111	Corporate Managers And Senior Officials
		112	Production Managers
		113	Functional Managers
		114	Quality and Customer Care Managers
		115	Financial Institution And Office Managers
		116	Managers In Distribution, Storage And Retailing
		117	Protective Service Officers
		118	Health and Social Services Managers
		121	Managers In Farming, Horticulture, Forestry And Fishing
		122	Managers And Proprietors In Hospitality And Leisure Services
		123	Managers And Proprietors In Other Service Industries
2	Business, Science, Technology and Public Service Professionals	211	Science Professionals
		212	Engineering Professionals
		213	Information And Communication Technology Professionals
		241	Legal Professionals
		242	Business And Statistical Professionals
		243	Architects, Town Planners, Surveyors
		244	Public Service Professionals
		245	Librarians And Related Professionals
3	Business, Science, Technology and Public Service Associate Professionals	311	Science And Engineering Technicians
		312	Draughts persons And Building Inspectors
		313	IT Service Delivery Occupations
		331	Protective Service Occupations
		341	Artistic And Literary Occupations
		342	Design Associate Professionals
		343	Media Associate Professionals
		344	Sports And Fitness Occupations
		351	Transport Associate Professionals
		352	Legal Associate Professionals
		353	Business And Finance Associate Professionals
		354	Sales And Related Associate Professionals
		355	Conservation Associate Professionals
		356	Public Service And Other Associate Professionals
4	Administrative and Secretarial	411	Administrative: Government and Related Organizations
		412	Administrative: Finance
		413	Administrative: Records
		414	Administrative: Communications
		415	Administrative: General
		421	Secretarial And Related Occupations
5	Skilled Trades	511	Agricultural Trades
		521	Metal Forming, Welding And Related Trades

(continued)

Table A1—(continued)

		522	Metal Machining, Fitting And Instrument Making Trades
		523	Vehicle Trades
		524	Electrical Trades
		531	Construction Trades
		532	Building Trades
		541	Textiles And Garments Trades
		542	Printing Trades
		543	Food Preparation Trades
		549	Skilled Trades n. e. c.
6	Personal Service	611	Healthcare And Related Personal Services
		612	Childcare And Related Personal Services
		613	Animal Care Services
		621	Leisure And Travel Service Occupations
		622	Hairdressers And Related Occupations
		623	Housekeeping Occupations
		629	Personal Services Occupations n. e. c.
7	Sales and Customer Service	711	Sales Assistants And Retail Cashiers
		712	Sales Related Occupations
		721	Customer Service Occupations
8	Process, Plant and Machine Operatives	811	Process Operatives
		812	Plant And Machine Operatives
		813	Assemblers And Routine Operatives
		814	Construction Operatives
		821	Transport Drivers And Operatives
		822	Mobile Machine Drivers And Operatives
9	Elementary	911	Elementary Agricultural Occupations
		912	Elementary Construction Occupations
		913	Elementary Process Plant Occupations
		914	Elementary Goods Storage Occupations
		921	Elementary Administration Occupations
		922	Elementary Personal Services Occupations
		923	Elementary Cleaning Occupations
		924	Elementary Security Occupations
		925	Elementary Sales Occupations
22, 23	Health, Teaching and Research Professionals	221	Health Professionals
		231	Teaching Professionals
		232	Research Professionals
32	Health and Social Welfare Associate Professionals	321	Health Associate Professionals
		322	Therapists
		323	Social Welfare Associate Professionals

Source: Office of National Statistics U.K.

Table A2—Facets of Noncognitive Skills

Personality trait	Questions used to create each of the five personality traits in column (1)
Openness to Experience	Motivated to academic achievement [a]
	Fearful of new situations/conditions [R]
Conscientiousness	Destroys property of others [b, R]
	Disobedient [b, R]
	Lazy – Hardworking [c, R]
	Never take work seriously [c]
Extraversion	Apathetic / Unresponsive [b, R]
	Solitary [b]
	Sociable – Withdrawn [c]
Agreeableness	Quarrelsome [b]
	Bullies other children [b]
	Timid – Aggressive [c]
Neuroticism	Restless [b]
	Squirmy / Fidgety [b]
	Irritable [b]
	Miserable [b]
	Cannot settle down [b]
	Moody [b]
	I get easily upset or irritated [b]
	I am frightened of going out alone/meeting people [b]
	I feel that often people annoy and irritate me [b]

[R] The answers have been reversed before being included in the final index using information from age16 of NCDS.
[a] Responses are on a scale from 0 to 40.
[b] Responses are ranked on a Likert scale from 1 to 3, where 1 corresponds to does not apply, 2 somewhat applies and 3 certainly applies.
[c] Responses range between 1 and 5 with 1 indicating strongly agree and 5 indicating strongly disagree.