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Preferences, comparative advantage, and compensating wage differentials for job routinization*

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Abstract

In this paper I attempt to explain why labor economists typically have not been able to find much evidence on compensating wage differentials for job disamenities, except for risk of death. The key insight here is that, although workers need to be compensated when their preferences do not match the requirements for performing a job task, the occurrence of mismatch also decreases productivity, reducing the surplus to be divided between workers and firms, and decreasing wages. I focus on the match between workers' preferences for routine jobs and the variability in tasks associated with the job. Using data from the Wisconsin Longitudinal Study, I find that mismatched workers earn lower wages and that both male and female workers in routinized jobs earn, on average, 5.5% and 7% less than their counterparts in non-routinized jobs. However, once preferences and mismatch are accounted for, this difference decreases to 2% for men and 4% for women. These findings suggest that accounting for mismatch is important when analyzing compensating wage differentials.

Keywords: compensating wage differentials, preferences, comparative advantage, mismatch, routine

JEL Classification: J3, J31

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1. Introduction

For more than thirty years, labor economists have been trying to find evidence of wage premiums for jobs that involve such disamenities as physical effort, routine nature of the work, or job insecurity. According to the theory of compensating wage differentials, which goes back to Adam Smith and involves the framework of analysis outlined by Rosen (1974), workers must receive a wage premium for suffering from job disamenities, ceteris paribus. However, a survey of the evidence has concluded that "*tests of the theory of compensating wage differentials are inconclusive with respect to every job characteristic except risk of death*" (Borjas, 2005, Chapter 6, p. 224, italics added).

It is obvious that on-the-job risk of death is an undesirable job characteristic, and the available empirical evidence indeed suggests that wages are positively associated with on-the-job risk of death (Viscusi and Aldy, 2003). However, many other job characteristics are not regarded as intrinsically undesirable by all workers. Instead, the desirability of a large number of job attributes depends crucially on individual workers' tastes or personalities. Smith (1979) notes that the heterogeneity of worker tastes make testing for compensating wage differentials difficult.

At first glance, preference heterogeneity may seem consistent with mixed results for repetitive work. For example, Lucas (1977) finds evidence of significant compensation for repetitive work, while Brown (1980) reports a negative estimate. Almost twenty years later, the mixed results are even more striking. Daniel and Sofer (1998) present some such results in their paper.

One straightforward way to account for preference heterogeneity when looking for compensating wage differentials is to run separate wage regressions for workers with different preferences. Still, as I show in the next section, non-routine-preferring workers earn lower wages in routinized jobs, which is contrary to what the theory of compensating wage differentials would predict. Therefore, preference heterogeneity by itself does not explain the puzzle of compensating wage differentials.

Why, even after accounting for preference heterogeneity, are compensating wage differentials not observed or incorrectly signed? What if workers' preferences for one type of job (or job attribute) are related to their productivity in performing that type of job? Workers' tastes for a certain job attribute may correlate with their comparative advantage in such jobs. This is not the same as saying that preferences can have a direct effect on wages, independent of the type of job; i.e., workers with different preferences may have different absolute advantages in performing any job. Rather, the key insight here is that when workers' preferences do not match job attributes, they are less productive. For example, non-routine-preferring workers are likely to be more productive in non-routinized jobs than routine-preferring workers. By the same token, routine-preferring workers are likely to be more productive in routinized jobs than non-routine-preferring workers.

If matching were perfect and each worker was assigned to a job according to comparative advantage, then the marginal routine-preferring worker would be willing to pay for working in a routinized job. Similarly, the marginal non-routine-preferring worker would need to be compensated for working in a routinized job. This would be consistent with the compensating wage differentials theory.

However, as Lang and Majumdar (2004) pointed out, both casual empiricism and research show that matching is imperfect. More recently, Shimer (2007) acknowledges that skills and geographical location of workers are poorly matched with the skill requirement and location of jobs: unemployed workers are attached to an occupation and a geographic location where jobs with their skills are currently scarce.

Here, a similar point can be made. As I will show, a mismatch between workers' preferences and job attributes does exist, and must be taken into account when looking for compensating wage differentials. Indeed, my findings indicate that not accounting for mismatch in wage equations could bias compensating wage differentials estimates.

I propose a simple assignment model with Nash bargaining over wages for analyzing the role of mismatch when looking for compensating wage differentials. Assuming that observed workers are not in long-run market equilibrium, all workers, no matter what their preferences are, need to be compensated if working in the sector with a shortage of workers in the absence of pay differentials. However, only mismatched workers, who are less productive because their sectors do not match their preferences, are penalized.

This simple framework offers a rationale for the existence of mixed estimates for compensating wage differentials. Indeed, in the literature the standard estimates may confound the effect on wages of the job attribute being analyzed with the one attributable to mismatch.

This paper focuses on job routinization (i.e., jobs involving repetitive and routine tasks). I consider this is an important job attribute to study because estimates for it in the literature are mixed (e.g., Lucas, 1977, Brown, 1980, Daniel and Sofer, 1998). So, this analysis may shed new light on the sources of these mixed results. Furthermore, Table 1 shows that 29% of male workers and 36% of female workers report that "being able to do different things rather than the same things over and over" is "much more important than high pay". Indeed, the Table indicates that variability of tasks is one of the most highly valued characteristics on the job for workers. This suggests that it should be easier to find compensating wage differentials for job routinization than for other job attributes.

Using data from the Wisconsin Longitudinal Study (WLS), I find that mismatched workers earn lower wages. My results also indicate that accounting for mismatch is important in obtaining more reliable estimates of compensating wage differentials. On average, male workers in routinized jobs are paid 5.5% less than workers in non-routinized jobs, after accounting for: differences in completed years of education, IQ measured at high school, high school rank, adult cognition, tenure, occupation and firm size. This difference decreases to 4.5% after accounting for differences in the preference for routine work. Furthermore, controlling for mismatch reduces the difference in average wages between male workers in routinized versus non-routinized jobs to 2%. For female workers, the difference decreases from 7% to 4%.

This paper is laid out as follows. Section 2 briefly describes the puzzle. It presents a brief review of the compensating wage differentials literature, offers a description of the WLS dataset, and takes a first look at the data. Section 3 presents a model that sheds light on the puzzle. Section 4 offers the empirical model. My results are in Section 5. Section 6 offers some robustness checks. Finally, Section 7 concludes.

2. The Puzzle

2.1. A Brief Review

More than two centuries ago, Adam Smith noted that workers with the same level of competence should be paid different wages if their working conditions are different. Rosen (1974) formalizes Adam Smith's ideas showing that, under perfect competition, identical workers need to be compensated for job disamenities.

The standard method for testing the prediction of this theory is to estimate a wage equation with characteristics of the job (z) and personal characteristics (p). In general, the equation is of the form:

$$\ln(w) = \alpha + \beta z + \rho p + \varepsilon \quad (1)$$

The estimation of (1) using cross-sectional data identifies a market relationship between $\ln(w)$ and z. If the market relationship is linear, then β measures the marginal cost of the disamenity for any worker who is in his most preferred job in long-run market equilibrium. For an undesirable job attribute, the theory predicts that $\beta > 0$. However, the empirical evidence on compensating wage differentials is mixed for job characteristics other than the risk of death (see Rosen (1986) for a classical discussion on the theory of equalizing differences).

There have been several previous attempts at solving this puzzle. First, the estimates may suffer from selection bias: workers choosing a job with a specific undesirable attribute may have less distaste for such an attribute (e.g., Kostiuk, 1990). Second, working conditions are endogenously determined: richer individuals are more able to bargain over working conditions than poorer individuals (e.g., Garen, 1988). Third, omitted variables can also lead to biased estimates because of the correlation between unobserved skills, individual productivities, and the quality of working conditions (e.g., Brown, 1980, Duncan and Holmlund, 1983, Hwang, Reed and Hubard, 1992). Fourth, when working conditions are reported by the workers themselves, the estimates are likely to suffer from simultaneity bias (e.g., McNabb, 1989). Further, if answers to survey questions about working conditions are given in subjective terms, then the estimates are likely to suffer from subjectivity biases (e.g., McNabb, 1989). Finally, when worker conditions are defined using average occupation (or industry) characteristics and then matched to individual workers, misclassification bias may arise.

From an empirical perspective, in this paper I take into account most of these biases. First, I control for preferences in my wage regressions to account for selection bias. Second, I use IQ measured at high school and high school rank as proxies for unobserved skills and individual productivities, and occupation and size of firm dummy variables to account for characteristics other than job routinization (the job attribute under study) that may be related to worker productivities. Third, job routinization is measured by time spent doing monotone tasks in order to circumvent the problem of subjectivity biases due to the use of answers given in subjective terms. Last but not least, I measure working conditions at the worker level, not at the occupation level, to avoid misclassification bias.

From a theoretical point of view, this paper can be thought of as looking at the consequence of the possibility that observed workers are not in a long-run equilibrium. I present a very simple model: workers are randomly assigned to jobs and wages are determined by Nash bargaining. The model highlights the effect of mismatch on wages, which must be taken into account when looking for compensating wage differentials.

I start by presenting the implications of preference heterogeneity (about the attractive or unattractive features of performing a job task) for estimates of compensating wage differentials. Suppose there are two types of workers: those who enjoy z $(x = 1)$ and those who have distaste for z $(x = 0)$. In that case, to test the theory of compensating wage differentials, the following regressions should be run:

$$\ln(w) = \alpha_0 + \beta_0 z + \rho_0 p + \varepsilon_0 \quad \text{if} \quad x = 0 \tag{2}$$

$$\ln(w) = \alpha_1 + \beta_1 z + \rho_1 p + \varepsilon_1 \quad \text{if} \quad x = 1 \tag{3}$$

If the theory is correct, I should find evidence on $\beta_0 > 0$ and $\beta_1 < 0$: workers who have distaste for z $(x = 0)$ are compensated for working in a job involving high levels of z, while workers who enjoy z $(x = 1)$ are willing to pay for working in a job involving high levels of z. With these predictions at hand, I can assess the existence of compensating wage differentials for job routinization depending on workers' preferences. Before taking a first look at the data, I provide a description of the dataset used in this paper.

2.2. Data

I use data from the Wisconsin Longitudinal Study (WLS) of the University of Wisconsin-Madison. The sample contains information on 10,317 men and women who graduated from Wisconsin high schools in 1957, approximately one-third of all seniors in Wisconsin high schools in 1957. It contains a rich set of self-reported information from sample members, siblings, and parents, as well as administrative data, collected in a series of surveys: 1957 (graduates), 1964 (graduates), 1975 (graduates), 1977 (siblings), 1992-3 (graduates), 1993-4 (siblings) and 2003-5 (graduates and spouses).

I focus on the 1992-3 waves, when respondents were in their early fifties. This decision is based on both informational requirements and sample (size and selectivity) considerations. First of all, information on workers' preferences is not available prior to the 1992-3 waves. Second, participation in the labor market is higher for people in their fifties (1992-3 waves) than in their sixties (2003-5 waves): 92.4% of men were employed in 1992 while only 47.8% of them were employed in 2004. Finally, this helps me to minimize non-random attrition problems.

The WLS dataset offers an opportunity for exploring the role of mismatch in observing compensating wage differentials. It contains a set of individual characteristics obtained from the (graduate) respondents, such as IQ score measured at high school, high school rank, adult cognition, education, tenure, preference for job routinization, hourly wages, hours of work, number of hours performing different tasks on the job, etc. Moreover, the sample is quite homogeneous (high school graduates from Wisconsin high schools in 1957), which makes any concerns about omitted variables less important.

My sample is restricted to workers who were employed in 1992. Unfortunately, employment status is missing for 1,824 individuals. This implies a dramatic decrease in the original sample size from 10,317 to 8,493. There are 7,196 individuals employed in 1992. After restricting our sample size to those individuals having a positive hourly wage rate, the number of observations decreases to 6,756. Focusing only on Wisconsin residents, the sample decreases to 4,696. The sample also excludes individuals who were: working less than 20 hours per week, self-employed, employees of their own company, or family workers. Farm workers and members of the military also are excluded from my sample. After applying these restrictions, my working sample is left with approximately 3,800 observations. The presence of extreme values in the wage distribution was detected accidentally through the comparison of average wages for men and women. To avoid the estimates being driven by extreme values in the wage distribution, I trim the tails of the log-wage distribution at both the 3% bottom and the 3% top. Finally, after dealing with missing observations for the variables used in the analysis, the working sample size is about 3,200. The next subsection presents the definition of the main variables used in the empirical analysis.

2.3. Definition of the Main Variables

The main variables in this paper are job routinization; worker's preference for routine; and mismatch, i.e., the discrepancy between job routinization and worker's preference for routine. In this subsection, I discuss how these variables are measured.

The **job routinization** indicator (z) —whether a job is classified as routinized or non-routinized— is constructed using the fraction of working time doing the same things over and over: job routinization is measured as 1 (routinized job) if the fraction of working time doing the same things over and over is equal to or higher than 0.5. Sensitivity analyses with alternative definitions of job routinization will be performed in the robustness checks section. I compute this fraction as the ratio of the number of weekly hours doing the same things over and over on the job to the total number of weekly working hours. Note that the reported number of hours can be compared across individuals; this addresses standard subjectivity bias concerns due to workers' subjective assessments about working conditions. Moreover, the fact that the number of hours worked is reported by the workers themselves confronts the misclassification bias that is attributable to imprecise matching of average job (occupation or industry) characteristics to individuals whose job characteristics may depart (by and large) from the average characteristics within their occupation or industry. Of course, as in previous studies, simultaneity biases may exist: workers who are unhappy with earnings that they receive may also respond negatively when asked about job attributes (McNabb, 1989).

The **worker's preference for routine** indicator (x) —whether a worker is classified as a routine-preferring worker or a non-routine-preferring worker— is measured by the response to this question: "To what extent do you see yourself as someone who prefers work that is routine and simple?" The possible answers to this question are: agree strongly, agree moderately, agree slightly, neither agree nor disagree, disagree slightly, disagree moderately, disagree strongly. This is one of the questions asked in scoring the Five-Factor Model of Personality Structure, and it is included in the personality section of the 1992-3 questionnaire, separate from job history or current/last job characteristics. Hence, the potential concerns about framing effects are minimized. For workers who agree strongly, moderately, or slightly, preferring work that is routine and simple, $x = 1$. Sensitivity analyses with alternative definitions of worker's preference for routine will be performed in the robustness checks section.

Finally, **mismatch** between job routinization and worker's preference for routine and simple work is measured as the absolute value of the difference between z and x, $m(z, x) = |z - x|$. I adopt this approach because absolute value seems to be the most intuitive way of thinking about the discrepancy between two variables. Note that for binary indicators, the absolute-value deviation is equivalent to the quadratic deviation.

2.4. Descriptive Statistics

Table 2 presents the main descriptive statistics of the WLS sample for currently employed individuals (1992-3). A first glance at the Table shows that, on average, male workers in non-routinized jobs earn $18.09 per hour, while male workers in routinized jobs earn $15.21: a difference of approximately $3 in the hourly wage. Women in non-routinized jobs earn $11.41 per hour, while women in routinized jobs earn $9.33. Although these are unadjusted averages, workers do not seem to be compensated for job routinization.

The Table also shows that the majority of men (52%) work in non-routinized jobs, while the majority of women work in routinized jobs (64%). At the same time, the fraction of workers who prefer routine and simple work is higher for women than for men: 0.24 versus 0.18. The fact that workers in non-routinized jobs are not compensated for job routinization is even more striking given that the supply of routine-preferring workers seems to be very low (24% of male workers, 18% of female workers) in comparison to the demand for them (48% of male workers, 64% of female workers).

Can mismatch explain the apparent lower wages in routinized jobs? The percentages of well-matched workers (according to job routinization and preference for routine and simple work) are 62% and 53% for men and women, respectively. Hence, mismatch is higher for women (47%) than for men (38%). For both men and women, mismatch is very high. Moreover, mismatch may be responsible for (part of) the difference in average wages between routinized and non-routinized jobs: mismatched men are paid \$15.51 per hour while those who are well-matched are paid \$17.44 per hour. For women the difference is smaller: \$9.61 versus \$10.53.

As expected, men are paid higher hourly wages than women: \$16.71 versus \$10.09. Not surprisingly, given the cohort under study, born around 1940, women on average are less educated than men.

Table 3 shows the distribution of workers (by their preferences for routine and simple work) across jobs (by routinization) and the average hourly wages by worker-job type. Among men, 42% of non-routine-preferring workers are mismatched into routinized jobs (567/1359*100), while this percentage is 57 for women (758/1331*100). For both men and women, the percentage of mismatched workers is lower in non-routinized jobs. This is consistent with the fact that the majority of men and women are non-routine-preferring workers (76% of men, and 82% of women). Regarding the average hourly wage, the Table describes an interesting feature of my data: there are no differences in average wages between mismatched and well-matched routine workers. Indeed, the differences are found only for non-routine-preferring workers.

2.5. A First Look at the Data

I start by measuring job routinization as the fraction of time at work doing the same things over and over. Routine-preferring workers ($x = 1$) are defined as those individuals who strongly agree, moderately agree, slightly agree, or neither agree nor disagree, with the statement “I see myself as someone who prefers work that is routine and simple”.

Table 4 reports the degree of job routinization by occupational category for men and women, respectively. As the Table makes clear, “Professional and Technical Specialty Operations”, and “Executive, Administrative, and Managerial” occupational categories on average involve less routinization, while occupations such as “Operators and Fabricators” involve more routinization of tasks. Another interesting feature that emerges from this Table is that female workers tend to spend a higher fraction of time than male workers doing the same things over and over. In other words, women tend to do more routinized tasks than men within occupational categories.

The results from Table 5 show evidence contrary to the theory of compensating wage differentials: workers with lower preferences for routine and simple work earn lower wages in the routinized jobs. Columns (2) and (4) show that both non-routine-preferring male and female workers do not appear to be compensated for working in routinized jobs; rather, if anything, they appear to be penalized. For routine-preferring workers, columns (1) and (3), I find a positive but not statistically significant association between job routinization and hourly wages.

The bottom line of Table 5 is that preference heterogeneity clearly matters, but in a surprisingly opposite way to what one would have expected from a selection-bias explanation: workers with lower preference for routine and simple work earn lower wages in routinized jobs. This paper provides an explanation for such a finding.

Notice that the implicit assumption behind the prediction of a positive association between job routinization and wages for non-routine-preferring workers is that they must be compensated because of their higher disutility when working in routinized jobs. However, non-routine-preferring workers are likely to be less productive in routinized jobs. In other words, workers' preferences are likely to reflect two things that are equally important for wage determination: their disutility from working, which will be higher as the discrepancy between preferences and job attributes (characteristics or job tasks) increases; and their comparative advantage on the job, which will be lower as the discrepancy between preferences and job attributes increases.

If matching were perfect, and each worker was assigned to a job according to her comparative advantage, then the productivity effect of comparative advantage would not play any role: productivity would be the same for every worker, because every worker would be assigned to a job where her comparative advantage was maximized. However, matching is far from perfect, and neglecting its influence on wages is likely to confound the compensating wage differentials estimates. In other words, (2) and (3) would be mis-specified if mismatch also matters.

Thus, a potential explanation for the puzzling results in Table 5 is that preferences for performing a job and the worker's comparative advantage in performing it are (positively) correlated. If this is the case, then workers with lower preference for routine and simple work will earn lower wages in routinized jobs, not because they are not compensated for taking such jobs but because they are less productive in performing them.

3. Conceptual Framework

In this section I present a simple assignment model with Nash bargaining to show the effect of mismatch on the wage rate. The main purpose of the model is to show the importance of the mismatch productivity effect on the wage rate, and its relevance for understanding estimates of compensating wage differentials.

There are two types of workers $x \in \{0,1\}$, defined by their preferences for a job attribute ($x = 0$ for non-routine preferring workers, $x = 1$ for routine-preferring workers) and a continuum of firms' types $z \in [0,1]$, defined by the job attribute ($z = 0$ for completely non-routinized jobs, and $z = 1$ for completely routinized jobs). Each firm is randomly matched with each worker: (z, x) for each firm-worker pair. Then, the firm z and the worker x bargain over the division of the match surplus to decide the optimal wage.

The profit function of the firm is given by

$$\pi = A\big(m(z, x)\big) - w \tag{4}$$

where A is gross revenue (production), which depends negatively on mismatch $m(z, x)$, and w is the wage rate. The negative relationship between A and m is assumed on the grounds that the worker's taste for a job attribute (e.g., routine-preferring worker) is likely to be positively correlated with his ability to perform well in a job with such an attribute (e.g., routinized job). In other words, a routine-preferring worker will tend to have a comparative advantage in doing repetitive things. Tinbergen (1975) sets a production function that depends on the extent to which a person's abilities match those required in the execution of a job task.

The utility function of the worker is given by

$$u = w - v\big(z, m(z,x)\big) \tag{5}$$

where v is the disutility from work, which depends positively on mismatch $m(z,x)$ between the job characteristic (z) and the worker's preference for such a job characteristic (x), and on the job characteristic (z).

This random assignment setting can be understood by assuming that due to fractions the market is not in long-run equilibrium. This is a plausible assumption since the data suggest that mismatch is substantial: 18% of male workers are classified as routine-prefer workers, while 48% of them are working in jobs involving half (or more) of their weekly time doing the same things over and over. Hence, I assume that the routinized sector is the sector with a shortage of workers in the absence of pay differentials, $\frac{\partial v(z,m(z,x))}{\partial z} > 0$.

The solution to the Nash bargaining problem is obtained from

$$\max_{w}\{\pi^{\theta} u^{1-\theta}\} \tag{6}$$

where $0 < \theta < 1$ measures the firm bargaining power.

The FOC gives us the optimal wage rate:

$$w^{*}(z, m(z,x)) = \theta v\big(z, m(z,x)\big) + (1-\theta)A\big(m(z,x)\big) \tag{7}$$

The marginal effect of z holding m constant, which is the "standard" compensating wage differential, is

$$\frac{\partial w^{*}(z, m(z,x))}{\partial z} = \theta \frac{\partial v\big(z, m(z,x)\big)}{\partial z} \tag{8}$$

which is positive given my previous assumption.

However, the total effect of z holding x constant is

$$\frac{dw^*(z, m(z, x))}{dz} = \frac{\partial w^*(z, m(z, x))}{\partial z} + \frac{\partial w^*(z, m(z, x))}{\partial m(z, x)} \frac{\partial m(z, x)}{\partial z} \tag{9}$$

where $\frac{\partial w^*(z,m(z,x))}{\partial z} > 0$ from (8), $\frac{\partial m(z,x)}{\partial z} > 0$ if $x = 0$ (i.e., the higher is job routinization, the higher is the mismatch for a non-routine preferring worker), and $\frac{\partial m(z,x)}{\partial z} < 0$ if $x = 1$ (i.e., the higher is job routinization, the lower is the mismatch for a routine preferring worker).

Equation (9) gives us precisely the effects being estimated as β_0 and β_1 in equations (2) and (3), in which m is omitted. What is the sign of $\frac{\partial w^*(z,m(z,x))}{\partial m(z,x)}$? The answer to this question is given by proposition 1.

Proposition 1. When mismatch also affects gross revenue (output), it has an ambiguous effect on the wage rate. If the productivity effect dominates the disutility effect, then mismatch affects the wage rate negatively. If the reverse is the case, then mismatch affects the wage rate positively. If both effects cancel each other out, then mismatch has no effect on the wage rate.

Proof.

$$\frac{\partial w^*(z, m(z, x))}{\partial m} = \theta \underbrace{\frac{\partial v\big(z, m(z, x)\big)}{\partial m}}_{>0} + (1 - \theta) \underbrace{\frac{\partial A\big(m(z, x)\big)}{\partial m}}_{<0} \tag{10}$$

Hence, given proposition 1, we conclude that the total effect of z holding x constant is ambiguous[1].

[1] Borghans et al. (2006) show that the effect of people skills on wages (in the equilibrium assignment) can be decomposed into two effects: first, workers with more people skills earn more because they generate higher (net) revenue (productivity effect); second, workers with more people skills take jobs where people tasks are more important and these jobs pay less, all else equal (compensating wage differential effect).

4. Empirical Model

My model yields three parameters that are captured in (11): a routine sector main effect (the "standard" compensating wage differential, β); a routine-preferring worker main effect (the absolute advantage of this type of worker, γ); and a negative wage effect for workers who are in a sector other than the one they prefer (the negative productivity effect due to mismatch, δ).

$$\ln(w) = \alpha + \beta z + \gamma x + \delta m(z, x) + \varepsilon \tag{11}$$

To identify the effects of m and z, I need to be aware of the possibility that the error term ε is correlated with m and/or z. First, mismatch (m) is likely to be correlated with worker's ability: workers with worse skills are likely to be paid lower wages and to end up being mismatched. Second, the level of job routinization (z) could be correlated with worker's skills and skills requirements of the job: routine jobs are perhaps those requiring unskilled workers.

I measure relevant worker's characteristics that may be related to both wages and mismatch by education (completed years of education), IQ score measured at high school, high school rank, and an adult cognition measure which is based on eight of the fourteen items from the Weschler Adult Intelligence Scale (WAIS). To account for the relevant characteristics of the job that may be related to both wages and job routinization, I control for occupation dummy variables (the 8 occupational categories are described in Table 4). Notice that once I control for occupation, the unique variation used to identify the wage premium/penalty associated with job routinization is within-occupation variation. Further, I also control for size of firm dummy variables. Given this rich set of control variables (C'), it seems plausible to identify the effects of m and z by means of (12):

$$\ln(w) = \alpha + \beta z + \gamma x + \delta m(z, x) + C'\Pi + u \tag{12}$$

Finally, although I have a rich set of control variables that helps me to identify the effects of z and m, regression (12) contains worker's preferences (x), which may well be endogenously determined and thus may compromise the interpretation of my estimates: workers' preferences are likely to be affected by their labor market experience. More specifically, an individual's working experience on a particular job (tenure) is likely to affect his preferences for such a job. Although I do not have suitable data for assessing whether workers' preferences change over time, I try to overcome this shortcoming by controlling for tenure: keeping tenure constant, the effect of preferences on wages is obtained net of the effect of tenure on preferences. Hence, C' will also include tenure.

5. Results

5.1. Empirical Findings

Tables 6 and 7 present the results on the effect of job routinization on wages for men and women, respectively. Column (1) in Table 6 shows that, on average, male workers in routinized jobs earn 11% less than male workers in non-routinized jobs. Once the worker's preference for routine work is accounted for, this penalty is reduced to 10% (see column (2)). Column (3) shows that routinized jobs on average pay 7% less than non-routinized jobs when mismatch is controlled; on average, mismatched workers earn 4% less than well-matched workers. Hence, if mismatch is not accounted for, the negative effect of job routinization on wages is overestimated. Indeed, once mismatch is included as a new variable in the wage regression, I can explain a substantial portion of the incorrectly-signed estimate for job routinization.

While columns (1) to (3) control for worker heterogeneity, they do not account for job heterogeneity. In columns (4)-(6) I add both occupation and size of firm dummy variables into the previous specifications in an attempt to account for both kinds of heterogeneity. Notice that controlling for occupation is crucial to account for different skill requirements of the job. The results in columns (4)-(6) are qualitatively similar to those in columns (1)-(3): male workers in routinized jobs earn 5.5% less than their counterparts in non-routinized jobs (see column (4)). This penalty decreases to 4.5% once I adjust for differences in preferences (see column (5)). Finally, once workers' preferences and mismatch are accounted for, this difference is reduced to 2% (see column (6)). Moreover, this is not statistically different from zero.

Table 7 reports similar results for women. Accounting for differences in preferences slightly decreases the job-routinization wage penalty, from 10% to 8% (columns (1) and (2)), or from 7% to 6.5% (columns (4) and (5)). Again, adding mismatch into the model seems to be important: the effect of job routinization decreases from 8% to 3.5% (columns (2) and (3)), or from 6.5% to 4% (columns (5) and (6)). In none of the cases, the job routinization effect on wages is statistically significant once both preferences for routinization and mismatch are accounted for. Mismatched female workers earn 4% less than well-matched female workers.

Overall, two features of the data stand out. First, mismatch is negatively related to wages. This is consistent with both my assignment model and Borghans et al. (2007): people are most productive in jobs that match their style, and they earn less when they have to shift to other jobs. Indeed, I find a mismatch effect after accounting for worker type (worker's preference for routine work), job type (job routinization), and other observable characteristics at the worker, occupation and firm levels. Second, once mismatch is accounted for, the coefficient on job routinization is attenuated. The evident mismatch effect can explain a substantial portion (but not all) of the incorrectly-signed compensating differential for job routinization indicated in previous analyses. Indeed, in the models with occupation and size of firm dummy variables, the compensating differential for job routinization cannot be statistically distinguished from zero. In the next section, I perform several robustness checks to the use of alternative measures and the presence of outliers. Before presenting the results of my sensitivity analyses, it is important to discuss my results.

5.2. Discussion

My results show that accounting for mismatch explains a substantial portion (but not all) of the incorrectly-signed compensating differential for job routinization indicated in previous analyses. The fact that job routinization has still a negative sign could be reflecting that workers in routine jobs are less productive than workers in non-routine jobs. However, we control for different proxies for individual productivity such as education and IQ. Furthermore, in the most complete empirical models, the coefficient on job routinization is not statistically different from zero.

Regarding the estimated effect of mismatch on wages, it must be recognized that this could be picking up two different kinds of effects. On the one hand, mismatch can have a negative effect on productivity due to the discrepancy between worker's preferences for routine jobs and the variability in tasks associated with the job (Tinbergen (1975) sets a production function that depends on the extent to which a person's abilities match those required in the execution of a job task). On the other hand, mismatch may reflect unobserved worker's ability: mismatched workers could be less productive to start with. Unfortunately, I cannot disentangle these two effects in my paper. Nonetheless, the fact that mismatch must be accounted for in wage equations is an important one.

Future research could benefit from such a framework using new and better data that may help to disentangle these two effects by using quasi-experimental variation in mismatch. For example, plant closing could be used as an instrument for mismatch to identify the effect of mismatch on wages for "workers who have been displaced from a non-routine job to a routine one by plant closing".

6. Robustness Checks

This section addresses some potential concerns about my previous estimates: the use of alternative measures of job routinization, routine-preferring worker and mismatch, and the sensitivity of OLS estimates to outliers.

6.1. Alternative Measures

The discrete approach to measuring job routinization and workers' preferences is appealing because it is neat and clear cut. Unfortunately, it does not take full advantage of all the available information contained in my data. Moreover, the thresholds defining routine jobs and routine-preferring workers are arbitrary.

In this subsection, I start by exploiting the variability in workers' preferences and measures of job routinization. Here, job routinization is measured as a continuous variable; workers' preferences are measured by several binary indicators; and mismatch is measured as it is in the rest of the paper. More specifically, the new job routinization variable is the fraction of working time doing the same things over and over on the job (as in Table 5). Workers' preference for routine is captured by several binary indicators: Routine-Preferring Worker 1 (equal to 1 for workers who disagree strongly or moderately with the statement "I see myself as someone who prefers work that is routine and simple", zero otherwise); Routine-Preferring Worker 2 (equal to 1 for workers who agree slightly, neither agree nor disagree, or disagree slightly with the previous statement, zero otherwise); Routine-Preferring Worker 3 (equal to 1 for those workers who agree moderately or strongly with the previous statement, zero otherwise). Tables 8 and 9 present the new estimates using these alternative measures of job routinization and workers' preferences, where the omitted category is Routine-Preferring Worker 1. The new estimates are very similar to the previous ones: the negative association between wages and job routinization decreases dramatically after accounting for worker's preference and mismatch. The Tables also reveal a negative association between mismatch and wages for both men and women: on average, both mismatched female and male workers earn 3% less than their well-matched counterparts.

I also check the sensitivity of my estimates to the thresholds defining routine jobs and routine-preferring workers. Now, I classify a job as routinized if the fraction of time doing the same things over and over is above the third quartile on the distribution of the fraction of time. And, a worker is classified as routine-preferring if his score on the preference for routine and simple work is above the third quartile on the distribution of preferences. The new mismatch measure is the absolute value of the difference between these new alternative measures. I provide new estimates with these alternative definitions for men and women in Table 10. The new estimates are very similar.

For men, column (1) shows that workers in routinized jobs on average earn 7% less than their counterparts in non-routinized jobs. Column (2) shows that accounting for differences in preferences makes the wage penalty lower: almost 6%. Finally, adding mismatch into the model, column (3), decreases the wage penalty even further: 3%. Note too that being mismatched is associated with a wage penalty of 7%. Similar qualitative results are found for women in columns (4)-(6).

6.2. Sensitivity to Outliers

OLS estimates are known to be sensitive to outliers. In my analysis, I trimmed both the bottom 3% and the top 3% of the wage distribution in order to avoid the influence of extreme values. Here, I go one step further and perform a median Quantile regression analysis to make sure that my previous OLS estimates are not driven by extreme values of the wage distribution.

The new (median) estimates reported in Tables 11 and 12 are robust to outliers and very similar to my previous OLS estimates. In Table 11, column (1) shows that, at the median, male workers in routinized jobs earn 11% less than male workers in non-routinized jobs. Once the worker's preference for routine work is accounted for, this penalty is reduced to 9% (column (2)). Column (3) shows that routinized jobs at the median pay 5% less than non-routinized jobs when mismatch is controlled. Mismatched workers earn 6% less than well-matched workers. Table 12 shows similar results for women, columns (1)-(3).

To sum up, my results appear to be robust. Moreover, the rich set of covariates I consider in the WLS (education, IQ at high school, high school rank, cognition score, preferences, tenure, occupation type and size of firm) helps me to control to some extent for both workers' and job's heterogeneity. Nonetheless, it should be noted that the absence of comparable longitudinal information on job routinization and workers' preferences as well as the absence of any valid instruments prevents me from arguing that the associations I document are causal.

7. Conclusions

In this paper my goal has been to argue that previous estimates of compensating wage differentials are inconclusive because they do not account for the discrepancy between workers' preferences and job attributes. Both casual empiricism and research results suggest that this discrepancy indeed exists. In my sample, 38% of the men and 47% of the women appear to be mismatched.

I propose a simple assignment model with Nash bargaining over wages for analyzing the role of mismatch when looking for compensating wage differentials. Assuming that observed workers are not in long-run market equilibrium, all workers, no matter what their preferences are, need to be compensated if working in the sector with a shortage of workers in the absence of pay differentials. However, only mismatched workers, who are less productive because their sectors do not match their preferences, are penalized. If mismatch is not accounted, then the association between wages and job attributes may be picking up the correlation between job attributes, preferences, and mismatch.

My empirical analysis uses the Wisconsin Longitudinal Study (WLS) and focuses on job routinization (the fraction of working time spent doing the same things over and over). I report several findings. First, mismatch is negatively related to wages, which is consistent with the negative mismatch productivity effect dominating the positive compensating wage differential effect. Second, for both men and women, I find that the negative relationship between wages and job routinization is attenuated once mismatch and workers' preferences are accounted for. The evident mismatch effect can explain a substantial portion (but not all) of the incorrectly-signed compensating wage differential for job routinization that previous analyses have indicated.

In my view, this paper highlights the importance of accounting for mismatch when looking for compensating wage differentials. Clearly, much more work needs to be done on the theoretical front, for instance, by endogenizing mismatch. Nevertheless, I anticipate that as long as there are search frictions that ensure that some workers remain in jobs that are not optimal given the existing wage rates, the results of the assignment model presented here will generalize to a market setting. Given the substantial mismatch I find in the data, these sorts of frictions seem realistic.

Appendix

Table 1: Percentage of currently employed individuals reporting that job characteristic is much more important than high pay, WLS 1992-3.

Job characteristic	Men	Women
Being able to do different things rather than the same things over and over	29	36
Being able to work without frequent checking by a supervisor	22	27
Having the opportunity to get on-the-job training	18	25
Having a job that other people regard highly	7	11
Being able to avoid getting dirty on the job	2	6

Source: Table 2 in Andrew et al. (2006).

Table 2: Descriptive statistics.

	Men			Women		
	Obs.	Mean	SD	Obs.	Mean	SD
Hourly wage routinized jobs	800	15.21	4.98	1,111	9.33	3.46
Hourly wage non-routinized jobs	865	18.09	6.10	637	11.41	4.19
Job Routinization (z = 1 if fraction of weekly worked hours doing the same things over and over is equal or higher than 0.5, z = 0 otherwise)	1,665	0.48	0.50	1,748	0.64	0.48
Routine-Preferring Worker (Preference for routine and simple work: x = 1 if strongly/moderately/slightly agree, x = 0 if strongly/moderately/slightly/ disagree or neither agree nor disagree)	1,656	0.18	0.38	1,743	0.24	0.42
Mismatch, $\|z - x\|$	1,656	0.38	0.49	1,743	0.47	0.50
Fraction of weekly worked hours doing the same things over and over	1,665	0.48	0.38	1,748	0.61	0.37
Preferences for routine and simple work						
Strongly agree	94	0.06	--	108	0.06	--
Moderately agree	162	0.10	--	238	0.14	--
Slightly agree	35	0.02	--	48	0.03	--
Neither agree nor disagree	6	0.00	--	18	0.01	--
Slightly disagree	59	0.04	--	68	0.04	--
Moderately disagree	447	0.27	--	503	0.29	--
Strongly disagree	853	0.52	--	760	0.44	--

Table 2: (continued)

	Men			Women		
	Obs.	Mean	SD	Obs.	Mean	SD
Hourly wage mismatched workers	636	15.51	5.08	821	9.61	3.52
Hourly wage well-matched workers	1,020	17.44	6.04	922	10.53	4.12
Hourly wage	1,665	16.71	5.77	1,748	10.09	3.87
IQ (measured at high school)	1,665	98.95	14.35	1,748	100.10	13.89
High School Rank	1,543	41.59	27.03	1,636	57.04	27.21
Education (years of completed education)	1,665	13.44	2.19	1,748	12.93	1.71
Adult Cognition Score (WAIS)	1,653	7.47	2.78	1,739	7.62	2.63
Tenure	1,659	19.34	11.00	1,744	12.09	9.00

Note: Author’s calculations.

Table 3: Distribution of workers across jobs and average hourly wages by worker-job type, WLS 1992-3.

(Number of observations)	$z = 0$	$z = 1$
Male		
$x = 0$	48% 18.4 (792)	34% 15.7 (567)
$x = 1$	4% 14.3 (69)	14% 14.0 (228)
Female		
$x = 0$	33% 11.8 (573)	43% 9.7 (758)
$x = 1$	4% 8.4 (63)	20% 8.5 (349)

Note: Author's calculations.

Table 4: Fraction of weekly worked hours doing the same things over and over by occupational category, WLS 1992-3.

Occupational Category	Men	Women
Professional and Technical Specialty Occupations	0.27	0.46
Executive, Administrative and Managerial Occupations	0.27	0.41
Sales Occupations	0.54	0.70
Administrative Support Occupations (including clerical)	0.63	0.65
Precision Production, Craft, and Repair Occupations	0.44	0.83
Operators and Fabricators	0.79	0.86
Service Occupations	0.64	0.79
Handlers, Equipment Cleaners, Helpers, Laborers, Farm Operators, Farm Workers, and Related Occupations	0.73	0.90

Source: Author's calculations.

Table 5: Job routinization and wages by workers' preferences
OLS estimates for men and women.
Dependent variable: log(hourly wage)
Job Routinization = fraction of weekly worked hours doing the same things over and over

	Men		Women	
	Workers' Preferences		Workers' Preferences	
	Routine	Non Routine	Routine	Non Routine
	(1)	(2)	(3)	(4)
Job Routinization	0.035	–0.082	0.004	–0.096
	(0.052)	(0.024)	(0.046)	(0.016)
Completed Years of Education	0.044	0.032	0.042	0.016
	(0.016)	(0.005)	(0.015)	(0.006)
IQ Measured at High School	0.002	0.002	0.002	0.004
	(0.002)	(0.001)	(0.002)	(0.001)
High School Rank	0.000	0.000	–0.000	0.000
	(0.001)	(0.005)	(0.001)	(0.000)
Adult Cognition Score	–0.005	0.004	–0.002	0.001
	(0.007)	(0.003)	(0.006)	(0.004)
Tenure	0.009	0.008	0.016	0.013
	(0.002)	(0.001)	(0.002)	(0.001)
R^2	0.25	0.32	0.39	0.38
Number of Observations	270	1,253	378	1,243

Notes: Heteroskedasticity robust standard errors are reported in parentheses. All regressions include occupation dummy variables.

Table 6: Mismatch and compensating wage differentials.
OLS estimates for men.
Dependent variable: log(hourly wage)

	(1)	(2)	(3)	(4)	(5)	(6)
Job Routinization	–0.107	–0.095	–0.068	–0.053	–0.045	–0.023
	(0.016)	(0.016)	(0.022)	(0.016)	(0.016)	(0.021)
Routine-Preferring Worker	--	–0.073	–0.091	--	–0.056	–0.071
		(0.020)	(0.022)		(0.019)	(0.022)
Mismatch	--	--	–0.037	--	--	–0.031
			(0.022)			(0.021)
Completed Years of Education	0.049	0.049	0.048	0.033	0.033	0.033
	(0.003)	(0.004)	(0.004)	(0.005)	(0.005)	(0.005)
IQ Measured at High School	0.003	0.003	0.003	0.003	0.003	0.003
	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)
High School Rank	0.000	0.000	0.000	0.000	–0.000	–0.000
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Adult Cognition Score	0.006	0.005	0.005	0.003	0.002	0.002
	(0.003)	(0.003)	(0.003)	(0.003)	(0.003)	(0.003)
Tenure	0.008	0.008	0.008	0.007	0.007	0.007
	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)
Occupation dummy variables?	NO	NO	NO	YES	YES	YES
Firm Size dummy variables?	NO	NO	NO	YES	YES	YES
R^2	0.27	0.28	0.28	0.36	0.36	0.37
Adjusted R^2	0.27	0.27	0.28	0.35	0.36	0.36
Number of Observations	1,523	1,523	1,523	1,520	1,520	1,520

Notes: Heteroskedasticity robust standard errors are reported in parentheses.

Table 7: Mismatch and compensating wage differentials.
OLS estimates for women.
Dependent variable: log(hourly wage)

	(1)	(2)	(3)	(4)	(5)	(6)
Job Routinization	–0.100	–0.083	–0.034	–0.072	–0.064	–0.038
	(0.018)	(0.018)	(0.021)	(0.016)	(0.016)	(0.020)
Routine-Preferring Worker	--	–0.114	–0.157	--	–0.076	–0.099
		(0.018)	(0.021)		(0.017)	(0.019)
Mismatch	--	--	–0.071	--	--	–0.037
			(0.021)			(0.019)
Completed Years of Education	0.047	0.046	0.045	0.022	0.022	0.021
	(0.006)	(0.006)	(0.006)	(0.006)	(0.006)	(0.006)
IQ Measured at High School	0.005	0.005	0.005	0.004	0.004	0.004
	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)
High School Rank	0.000	–0.000	–0.000	0.000	0.000	0.000
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Adult Cognition Score	0.004	0.004	0.004	0.001	0.001	0.001
	(0.003)	(0.003)	(0.003)	(0.003)	(0.003)	(0.003)
Tenure	0.015	0.015	0.015	0.012	0.012	0.012
	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)
Occupation dummy variables?	NO	NO	NO	YES	YES	YES
Firm Size dummy variables?	NO	NO	NO	YES	YES	YES
R^2	0.31	0.32	0.32	0.44	0.45	0.45
Adjusted R^2	0.30	0.32	0.32	0.44	0.44	0.44
Number of Observations	1,621	1,621	1,621	1,612	1,612	1,612

Notes: Heteroskedasticity robust standard errors are reported in parentheses.

Table 8: Mismatch and compensating wage differentials.
OLS estimates for men.
Dependent variable: log(hourly wage)

	(1)	(2)	(3)	(4)	(5)	(6)
Job Routinization	–0.144	–0.125	–0.086	–0.071	–0.058	–0.029
	(0.021)	(0.022)	(0.027)	(0.022)	(0.022)	(0.027)
Routine-Preferring Worker 2	--	–0.052	–0.056	--	–0.046	–0.049
		(0.034)	(0.034)		(0.032)	(0.032)
Routine-Preferring Worker 3	--	–0.081	–0.104	--	–0.061	–0.078
		(0.022)	(0.024)		(0.021)	(0.023)
Mismatch	--	--	–0.046	--	--	–0.034
			(0.020)			(0.019)
Completed Years of Education	0.049	0.048	0.048	0.033	0.033	0.033
	(0.004)	(0.004)	(0.004)	(0.005)	(0.005)	(0.005)
IQ Measured at High School	0.003	0.003	0.002	0.002	0.002	0.002
	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)
High School Rank	0.000	0.000	0.000	0.000	–0.000	–0.000
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Adult Cognition Score	0.006	0.004	0.004	0.003	0.002	0.002
	(0.003)	(0.003)	(0.003)	(0.003)	(0.003)	(0.003)
Tenure	0.008	0.009	0.009	0.007	0.007	0.007
	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)
Occupation dummy variables?	NO	NO	NO	YES	YES	YES
Firm Size dummy variables?	NO	NO	NO	YES	YES	YES
R^2	0.27	0.28	0.28	0.36	0.36	0.36
Adjusted R^2	0.27	0.28	0.28	0.35	0.35	0.36
Number of Observations	1,523	1,523	1,523	1,520	1,520	1,520

Notes: Heteroskedasticity robust standard errors are reported in parentheses.

Table 9: Mismatch and compensating wage differentials.
OLS estimates for women.
Dependent variable: log(hourly wage)

	(1)	(2)	(3)	(4)	(5)	(6)
Job Routinization	–0.152	–0.126	–0.086	–0.106	–0.092	–0.068
	(0.023)	(0.023)	(0.027)	(0.022)	(0.022)	(0.025)
Routine-Preferring Worker 2	--	–0.075	–0.086	--	–0.047	–0.053
		(0.030)	(0.030)		(0.028)	(0.029)
Routine-Preferring Worker 3	--	–0.110	–0.142	--	–0.073	–0.092
		(0.019)	(0.022)		(0.018)	(0.020)
Mismatch	--	--	–0.051	--	--	–0.029
			(0.019)			(0.018)
Completed Years of Education	0.045	0.045	0.044	0.021	0.022	0.021
	(0.006)	(0.006)	(0.006)	(0.006)	(0.006)	(0.006)
IQ Measured at High School	0.005	0.005	0.005	0.004	0.004	0.004
	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)
High School Rank	–0.000	–0.000	–0.000	0.000	0.000	0.000
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Adult Cognition Score	0.004	0.004	0.004	0.001	0.001	0.001
	(0.003)	(0.003)	(0.003)	(0.003)	(0.003)	(0.003)
Tenure	0.015	0.015	0.015	0.012	0.012	0.012
	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)
Occupation dummy variables?	NO	NO	NO	YES	YES	YES
Firm Size dummy variables?	NO	NO	NO	YES	YES	YES
R^2	0.31	0.32	0.33	0.44	0.45	0.45
Adjusted R^2	0.31	0.32	0.32	0.44	0.44	0.44
Number of Observations	1,621	1,621	1,621	1,612	1,612	1,612

Notes: Heteroskedasticity robust standard errors are reported in parentheses.

Table 10: Mismatch and compensating wage differentials.
OLS estimates for men and women.
Dependent variable: log(hourly wage)

	Men			Women		
	(1)	(2)	(3)	(4)	(5)	(6)
Job Routinization	–0.071	–0.056	–0.030	–0.089	–0.072	–0.054
	(0.018)	(0.018)	(0.019)	(0.017)	(0.017)	(0.018)
Routine-Preferring Worker	--	–0.086	–0.070	--	–0.116	–0.114
		(0.019)	(0.020)		(0.018)	(0.018)
Mismatch	--	--	–0.067	--	--	–0.038
			(0.019)			(0.017)
Completed Years of Education	0.050	0.050	0.049	0.050	0.048	0.048
	(0.004)	(0.004)	(0.004)	(0.005)	(0.005)	(0.005)
IQ Measured at High School	0.003	0.003	0.003	0.006	0.005	0.005
	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)
High School Rank	0.000	0.000	0.000	0.000	–0.000	–0.000
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Adult Cognition Score	0.006	0.005	0.005	0.004	0.004	0.004
	(0.003)	(0.003)	(0.003)	(0.003)	(0.003)	(0.003)
Tenure	0.008	0.008	0.008	0.015	0.015	0.015
	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)
R^2	0.26	0.27	0.27	0.30	0.32	0.32
Number of Observations	1,523	1,523	1,523	1,621	1,621	1,621

Notes: Heteroskedasticity robust standard errors are reported in parentheses.

Table 11: Mismatch and compensating wage differentials.
Quantile Median estimates for men.
Dependent variable: log(hourly wage)

	(1)	(2)	(3)	(4)	(5)	(6)
Job Routinization	–0.108	–0.088	–0.049	–0.044	–0.037	–0.016
	(0.020)	(0.021)	(0.029)	(0.021)	(0.020)	(0.027)
Routine-Preferring Worker	--	–0.074	–0.107	--	–0.068	–0.087
		(0.025)	(0.030)		(0.020)	(0.026)
Mismatch	--	--	–0.060	--	--	–0.029
			(0.030)			(0.025)
Completed Years of Education	0.053	0.052	0.052	0.034	0.034	0.035
	(0.005)	(0.005)	(0.005)	(0.005)	(0.005)	(0.005)
IQ Measured at High School	0.003	0.003	0.002	0.003	0.003	0.003
	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)
High School Rank	0.000	0.000	0.000	–0.000	–0.000	–0.000
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Adult Cognition Score	0.007	0.005	0.006	0.001	0.003	0.003
	(0.004)	(0.004)	(0.004)	(0.004)	(0.004)	(0.003)
Tenure	0.008	0.008	0.008	0.006	0.006	0.006
	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)
Occupation dummy variables?	NO	NO	NO	YES	YES	YES
Firm Size dummy variables?	NO	NO	NO	YES	YES	YES
Pseudo R^2	0.16	0.17	0.17	0.22	0.22	0.22
Number of Observations	1,523	1,523	1,523	1,520	1,520	1,520

Notes: Bootstrapped standard errors (1,000 replications) are reported in parentheses.

Table 12: Mismatch and compensating wage differentials.
Quantile Median estimates for women.
Dependent variable: log(hourly wage)

	(1)	(2)	(3)	(4)	(5)	(6)
Job Routinization	–0.100	–0.089	–0.056	–0.070	–0.069	–0.037
	(0.024)	(0.022)	(0.027)	(0.022)	(0.021)	(0.024)
Routine-Preferring Worker	--	–0.134	–0.157	--	–0.074	–0.111
		(0.021)	(0.027)		(0.022)	(0.025)
Mismatch	--	--	–0.060	--	--	–0.052
			(0.026)			(0.022)
Completed Years of Education	0.064	0.063	0.063	0.032	0.032	0.030
	(0.007)	(0.007)	(0.007)	(0.007)	(0.007)	(0.007)
IQ Measured at High School	0.006	0.005	0.006	0.004	0.004	0.004
	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)
High School Rank	0.000	0.000	0.000	–0.000	–0.000	–0.000
	(0.001)	(0.001)	(0.000)	(0.001)	(0.001)	(0.001)
Adult Cognition Score	0.001	–0.003	–0.002	–0.001	–0.003	–0.002
	(0.005)	(0.006)	(0.006)	(0.004)	(0.004)	(0.004)
Tenure	0.016	0.017	0.017	0.013	0.014	0.014
	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)
Occupation dummy variables?	NO	NO	NO	YES	YES	YES
Firm Size dummy variables?	NO	NO	NO	YES	YES	YES
Pseudo R^2	0.20	0.21	0.21	0.30	0.30	0.30
Number of Observations	1,621	1,621	1,621	1,612	1,612	1,612

Notes: Bootstrapped standard errors (1,000 replications) are reported in parentheses.

References

Andrew, Megan, Shlomit Bornstein, Pascale Carayon, Deborah Carr, Heejeong Choi, John Delamater, Heather Doescher, Kathryn Flynn, Carl Frederick, Dan Fischer, Jeremy Freese, Hanna Grol-Prokopczyk, Robert M. Hauser, Taissa S. Hauser, Reiping Huang, Jeong Hwa Ho, Peter Hoonakker, Dmitry Khodyakov, David Merrill, Luke Piefer, Jane Piliavin, Tetyana Pudrovska, Elizabeth Rainwater, James Raymo, Carol Roan, Erin Ruel, Diane Shinberg, Kamil Sicinski, Erica Siegl, Kristen Springer, John Robert Warren, Erin Wicke, Alexandra Wright, and James Yonker (2006), "The Class of 1957 in their Mid-60s: A First Look," Hauser, Robert M. and Carol L. Roan, eds., Center for Demography and Ecology, University of Wisconsin-Madison, CDE Working Paper No. 2006-03.

Borghans, Lex, Bas ter Weel, and Bruce A. Weinberg (2006), "People People: Social Capital and the Labor-Market Outcomes of Underrepresented Groups," NBER Working Paper No. 11985.

Borghans, Lex, Bas ter Weel, and Bruce A. Weinberg (2007), "Interpersonal Styles and Labor Market Outcomes," NBER Working Paper No. 12846.

Borjas, George J. (2005), Labor Economics, Third Edition, New York: McGraw-Hill Irwin.

Brown, Charles (1980), "Equalizing Differences in the Labor Market," *Quarterly Journal of Economics*, 94(1), pp. 113–34.

Daniel, Christophe, and Catherine Sofer (1998), "Bargaining, Compensating Wage Differentials, and Dualism of the Labor Market: Theory and Evidence for France," *Journal of Labor Economics*, 16(3), pp. 546–75.

Duncan, Greg J., and Bertil Holmlund (1983), "Was Adam Smith Right After All? Another Test of the Theory of Compensating Wage Differentials," *Journal of Labor Economics*, 1(4), pp. 366–79.

Garen, John (1988), "Compensating Wage Differentials and the Endogeneity of Job Riskiness," *Review of Economics and Statistics*, 70(1), pp. 9–16.

Goldin, Claudia, Lawrence F. Katz, and Ilyana Kuziemko (2006), "The Homecoming of American College Women: The Reversal of the College Gender Gap," *Journal of Economic Perspectives*, 20(4), pp. 133–56.

Hwang, Hae-Shin, W. Robert Reed, and Carlton Hubbard (1992), "Compensating Wage Differentials and Unobserved Productivity," *Journal of Political Economy*, 100(4), pp. 835–58.

Kostiuk, Peter (1990), "Compensating Differentials for Shift Work," *Journal of Political Economy*, 98(5), pp. 1054–75.

Lang, Kevin, and Sumon Majumdar (2004), "The Pricing of Job Market Characteristics when Market Do Not Clear," *International Economic Review*, 45(4), pp. 1111–28.

Lucas, Robert E. B. (1977), "Hedonic Wage Equations and Psychic Wages in the Returns to Schooling," *American Economic Review*, 67(4), pp. 549–58.

McNabb, Robert (1989), "Compensating Wage Differentials: Some Evidence for Britain," *Oxford Economic Papers*, 41(2), pp. 327–38.

Mueller, Gerrit, and Erik Plug (2006), "Estimating the effect of personality on male and female earnings," *Industrial and Labor Relations Review*, 60(1), pp. 3–22.

Rosen, Sherwin (1974), "Hedonic Prices and Implicit Markets," *Journal of Political Economy*, 82(1), pp. 34–55.

Rosen, Sherwin (1986), "The Theory of Equalizing Differences," in Ashenfelter, Orley, and Richard Layard, eds., *Handbook of Labor Economics*, vol.1, Amsterdam, The Netherlands: Elsevier Science.

Shimer, Robert (2007), "Mismatch," *American Economic Review*, 97(4), pp. 1074–101.

Smith, Robert S. (1979), "Compensating Wage Differentials and Public Policy: A Review," *Industrial and Labor Relations Review*, 32(3), pp. 339–52.

Tinbergen, Jan (1975), Income Distribution: Analysis and Policies, Amsterdam: North Holland Co.

Viscusi, W. Kip, and Joseph E. Aldy (2003), "The Value of a Statistical Life: A Critical Review of Market Estimates throughout the World," *Journal of Risk and Uncertainty*, 27(1), pp. 5–76.

Zax, Jeffrey S., and Daniel I. Rees (2002), "IQ, Academic Performance, Environment and Earnings," *Review of Economics and Statistics*, 84(4), pp. 600–16.

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