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**Preferences, Comparative Advantage, and Compensating Wage Differentials for
Job Routinization**

Climent Quintana-Domeque*
Princeton University

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ABSTRACT

I attempt to explain why compensating differentials for job disamenities are difficult to observe. 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 report lower job satisfaction and earn lower wages. Both male and female workers in routinized jobs earn, on average, 12% less than their counterparts in non-routinized jobs. Once preferences and mismatch are accounted for, this difference decreases to 8% for men and 5% for women. Accounting for mismatch is important when analyzing compensating differentials.

JEL codes: J30, J31

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Climent Quintana-Domeque
Industrial Relations Section
Princeton University
Princeton, NJ 08540

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? 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.

I propose a simple assignment model with Nash bargaining over wages for analyzing the role of mismatch on wages. If mismatch is simply a disamenity and has no effect on worker productivity, then my model is consistent with the standard prediction of the theory of compensating wage differentials: workers are compensated for being mismatched (i.e., there is a compensating wage differential effect). However, once mismatch is acknowledged to affect worker's output (productivity effect), its effect on the wage rate is ambiguous. Although workers need to be compensated when their preferences do not match the work requirements of performing a job task, the occurrence of mismatch also decreases their productivity, thus reducing the surplus to be divided between workers and firms, and ultimately decreasing wages.

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 and are less satisfied with their jobs than well-matched workers, as predicted by my model. 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 12% less than workers in non-routinized jobs, after accounting for: differences in IQ measured at high school, high school rank, firm size, and industry type. This difference decreases to 11% 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 8%. For female workers, the difference decreases from 12% to 5%.

This paper is laid out as follows. Section 2 briefly describes the puzzle in the compensating wage differentials literature. Section 3 presents a model that sheds light on the puzzle. Section 4 describes the WLS dataset and the econometric specifications and presents some descriptive statistics. My results are in Section 5. Section 6 offers some robustness checks. In Section 7 I discuss the caveats of my analysis. Finally, Section 8 concludes.

2. The Puzzle

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 disamenities¹.

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

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

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.

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 Hubbard, 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

¹ A classical discussion on the theory of equalizing differences is offered in Rosen (1986). Chapter 7 in Polacheck and Siebert (1999), Chapter 5 in Cahuc and Zylberberg (2004), and Chapter 6 in Borjas (2005), provide excellent reviews of the theory of compensating wage differentials.

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 a theoretical point of view, this paper can be thought of as an extension of the first explanation given above. Therefore, 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:

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

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

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.

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 2 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 3 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. Column (2) shows that non-routine-preferring male workers do not appear to be compensated for working in routinized jobs; rather, if anything, they appear to be penalized. The addition of several controls does not change this conclusion. Looking at the rest of even columns, from (4) to (16), I find the same result: for non-routine-preferring workers, on average, the higher is the fraction of working time doing the same things over and over, the lower is the hourly wage. For routine-preferring workers, I do not find a statistically significant association between job routinization and hourly wages. Similar conclusions can be drawn from Table 4 for women.

It is worth noting that controlling for education, IQ measured at high school, and high school rank seems to be a credible way of accounting for differences in workers’ abilities and skills. At the same time, controlling for firm size and industry type appears to be a reasonable strategy for accounting for technology differences across firms.

Moreover, a careful examination of Tables 3 and 4 reveals that the coefficients on the covariates are very similar for both groups of workers. Hence, it seems reasonable to argue that the results from these tables are not driven either by unobserved workers' abilities or by unobserved firms' technologies. Notice that the constant term in each group-of-worker-specific regression captures a fixed effect (e.g., fixed ability, α_0 and α_1 , respectively) for each group of workers.

The bottom line of Tables 3 and 4 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.

To better understand the estimates from Tables 3 and 4, consider the following case. There are two types of jobs ($z = \{0,1\}$) and two types of workers ($x = \{0,1\}$). Some workers and firms are matched with their types (0,0) and (1,1), while some others are mismatched (0,1) and (1,0). The econometric model is given by:

$$\ln(w) = \alpha + \beta z + \gamma x + \delta m(z, x) + \varepsilon \quad (4)$$

The mismatch measure m is equal to 1 if $z = x$, and 0 otherwise. Assuming that $E(\varepsilon|z, x) = 0$, Figure 1 summarizes the expected log wages for each worker-job pair.

Notice that the coefficients β_0 and β_1 in equations (2) and (3) are capturing two different effects in terms of the model in (4): $\beta_0 = \beta + \delta$ and $\beta_1 = \beta - \delta$, where δ is picking up the mismatch effect. If we are willing to assume that the compensating wage differential applies to anyone working in the routinized sector whether the worker prefers routine or non-routine work, but that the productivity effect applies only to workers who are mismatched, that is, whose sectors do not match their preferences, then β will capture the compensating wage differential effect while δ will capture the mismatch productivity effect.

Thus, a potential explanation for the puzzling results in Tables 3 and 4 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. Indeed, my estimates suggest that $\delta < 0$, and that the wage penalty associated with job routinization decreases by a large amount once mismatch is taken into account.

Tables 5 and 6 report similar estimates to those in Tables 3 and 4 but use a binary indicator for job routinization rather than a continuous variable.

3. The Model

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.

In my setting, workers and firms are randomly matched. One can think of a situation where workers are indifferent between different job alternatives because of search costs (due to informational asymmetries between firms and workers, or geographical dispersion of jobs and workers) and they randomly pick up one of the available jobs². Wage determination occurs through generalized Nash bargaining (interpretations of such a solution in terms of strategic bargaining theory are provided in Rogerson, Shimer and Wright, 2005). To simplify the problem, the threat points are assumed to be zero.

² In Shimer (2007) workers and jobs are randomly allocated to labor markets. My model simply assumes that each firm is randomly matched with each worker. Although it is beyond the scope of the paper to provide a rationale for the existence of mismatch, one can think of a situation with imbalances between labor supply and labor demand, informational asymmetries, or geographical dispersion as mismatch determinants. First, expansion or contraction of industries in response to changes in the demand for goods and services, new technologies introduced in the workplace, changes in the organization of work, etc., on the demand side, and demographic changes, changes in preferences across generations, etc., on the supply side, may lead to imbalances between labor supply and labor demand. Second, informational asymmetries between workers and firms and geographical dispersion of both workers and firms pose difficulties for the proper matching between specific jobs and specific workers. Acquiring information on both the available type of jobs and the available types of workers is costly. Mobility costs of geographical dispersion are also important.

To begin with, consider a static game where there is a continuum of workers' types $x \in [0,1]$ and a continuum of firms' types $z \in [0,1]$. Each firm is randomly matched with each worker: (z,x) for each firm-worker pair. Notice that the (z,x) pairs are not determined endogenously but rather taken as randomly given. Once the matching is complete, the firm z and the worker x bargain over the division of the match surplus to decide the optimal wage. Two cases can be distinguished: the benchmark case, with no mismatch productivity effect, and the new case, with mismatch productivity effect.

3.1. The Benchmark Case: mismatch is simply a disamenity

The profit function of the firm is given by

$$\pi = A - w \quad (5)$$

where A is gross revenue (production) and w is the wage rate.

The utility function of the worker is given by

$$u(m(z,x)) = w - v(m(z,x)) \quad (6)$$

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 x . Then mismatch can be seen as a disamenity, $v' > 0$. Tinbergen (1975) assumes utility to be determined by a quadratic loss function dependent upon discrepancies between job and personal attribute values.

The solution to the Nash bargaining problem is obtained from

$$\max_w \{ \pi^\theta u(m(z,x))^{1-\theta} \} \quad (7)$$

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

The FOC gives us the optimal wage rate:

$$w^*(m(z, x)) = \theta v(m(z, x)) + (1 - \theta)A \quad (8)$$

The benefits for the firm and the worker are:

$$\pi^*(m(z, x)) = \theta[A - v(m(z, x))] \quad (9)$$

$$u^*(m(z, x)) = (1 - \theta)[A - v(m(z, x))] \quad (10)$$

The effect of mismatch on the optimal wage rate is obtained from differentiating (8) with respect to $m(z, x)$:

$$\frac{\partial w^*(m(z, x))}{\partial m(z, x)} = \theta v'(m(z, x)) \quad (11)$$

Mismatch, which is a disamenity, does affect the wage rate positively ($v' > 0$). This is consistent with the standard prediction of the theory of compensating wage differentials.

3.2. The New Case: mismatch also affects productivity

In the previous case, mismatch only affects the disutility of work: mismatch plays the role of a pure disamenity. However, mismatch is also likely to affect the firm's gross revenue (output).

A worker can be compensated for the disutility of performing a routinized job because he has a distaste for repetitive things. This distaste is likely to be negatively correlated with his ability to do repetitive things, i.e., comparative advantage in doing repetitive things. In other words, the worker's taste or preference for a type of job and his comparative advantage on that type of job are likely to be positively correlated. In this more general case, the profit function of the firm may be rewritten as

$$\pi(m(z, x)) = A(m(z, x)) - w \quad (12)$$

where A is gross revenue (production), which now depends negatively on mismatch $m(z,x)$ between the job characteristic z and the worker's preference x , and w is the wage rate. Mismatch now also affects productivity: $A' < 0$. 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 still is given by (6), and the solution to the Nash bargaining problem must acknowledge that the profit function is different. Again, the FOC gives us the optimal wage rate:

$$w^*(m(z,x)) = \theta v(m(z,x)) + (1-\theta)A(m(z,x)) \quad (13)$$

The benefits for the firm and the worker are:

$$\pi^*(m(z,x)) = \theta[A(m(z,x)) - v(m(z,x))] \quad (14)$$

$$u^*(m(z,x)) = (1-\theta)[A(m(z,x)) - v(m(z,x))] \quad (15)$$

The effect of mismatch on the optimal wage rate comes from differentiating (13) with respect to $m(z,x)$:

$$\frac{\partial w^*(m(z,x))}{\partial m(z,x)} = \theta v'(m(z,x)) + (1-\theta)A'(m(z,x)) \quad (16)$$

The expression for the mismatch effect on the wage rate now has two different components. The first term in (16) is what I obtained in (11): it is positive ($v' > 0$) and measures the compensating wage differential effect due to mismatch. However, there is a new term that did not appear in (11): this term is negative ($A' < 0$) and measures the productivity effect due to mismatch. Hence, the total effect of mismatch is ambiguous³.

³ 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).

3.3. Main Implications of the Model

My model leads to two main propositions:

Proposition 1. When mismatch also affects gross revenue (output), it has an ambiguous effect on the wage rate. If the productivity effect dominates the compensating wage differential 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. See equation (16).

Proposition 2. Mismatch has a negative effect on utility.

Proof. $\frac{\partial u^*(m(z, x))}{\partial m(z, x)} = (1 - \theta)[A'(m(z, x)) - v'(m(z, x))] < 0$.

These propositions are investigated empirically in the results section.

3.4. Implications of the Model for Estimates of Compensating Wage Differentials

Note that in the previous model, each worker-firm pair bargains over the match surplus in order to decide the optimal wage. However, in a market setting, the optimal wage arises from the interaction between labor supply (workers) and demand (firms). Thus, one question arises immediately: what are the implications of my assignment model for standard compensating wage differentials that emerge from a market setting? To answer this, I need to make two assumptions.

First, I need to assume that the compensating wage differential applies to anyone working in the routinized sector (assuming that it is the sector with a shortage of workers in the absence of pay differentials), whether he prefers routine or non-routine work. By contrast, the productivity effect applies only to workers who are mismatched, whose

sectors do not match their preferences. Thus, my model yields three parameters that are captured in (4) and represented in Figure 1: **a routine sector main effect** (the 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).

Next, I need a key identifying assumption: the observation that a worker is mismatched does not provide any information about that worker's skill (i.e., his absolute advantage), once his preferences and other observable characteristics are controlled for. Given that I have a rich set of observables, including IQ scores, this seems a plausible assumption.

The estimates reported in Figure 1 are easy to follow with the model above. Nevertheless, it is helpful to reinterpret them in a standard difference-in-difference framework. Consider the following specification:

$$\ln(w) = \alpha^* + \beta^* z + \gamma^* x + \delta^* zx + \varepsilon^* \quad (17)$$

where $\delta^* = -2\delta > 0$.

Notice that the negative productivity effect of being mismatched corresponds to a positive interaction between a worker's taste for routinized work and the degree to which her observed job is routinized. Figure 2 can be compared with Figure 1.

Although I am going to focus on the analysis of estimates from specification (4), for the sake of comparison the estimates from specification (17) are reported in the robustness checks section.

4. Data and Econometric Specifications

I use data from the Wisconsin Longitudinal Study (WLS) of the University of Wisconsin-Madison⁴. 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, such as IQ score measured at high school, high school rank, education, preferences, wages, job satisfaction, hours of work, number of hours performing different tasks on the

⁴ This research uses data from the Wisconsin Longitudinal Study (WLS) of the University of Wisconsin-Madison. Since 1991, the WLS has been supported principally by the National Institute on Aging (AG-9775 and AG-21079), with additional support from the Vilas Estate Trust, the National Science Foundation, the Spencer Foundation, and the Graduate School of the University of Wisconsin-Madison. A public use file of data from the Wisconsin Longitudinal Study is available from the Wisconsin Longitudinal Study, University of Wisconsin-Madison, 1180 Observatory Drive, Madison, Wisconsin 53706 and at <http://www.ssc.wisc.edu/~wls/data/>. The opinions expressed herein are those of the authors. The WLS has been used before to estimate the returns associated with IQ (Zax and Rees, 2002) and personality traits (Mueller and Plug, 2006). Goldin, Katz and Kuziemko (2006) also use this dataset.

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 both Wisconsin residents and were employed in 1992, and it 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. 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.

4.1. 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. 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 industry⁵.

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, $x = 1$.

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.

⁵ Of course, simultaneity biases may exist: workers who are unhappy with earnings that they receive may also respond negatively when asked about job attributes (McNabb, 1989).

4.2. Econometric Specifications

My model establishes two main results. First, the relationship between the wage rate and mismatch is given by:

$$w^*(m(z, x)) = \theta v(m(z, x)) + (1 - \theta) A(m(z, x)) \quad (18)$$

As Proposition 1 states, depending on the size of the mismatch productivity effect relative to the mismatch compensating-wage-differential effect, the effect on the wage rate will be positive, negative, or zero. Hence, the baseline empirical specification, after a log-linearization of (18), to investigate Proposition 1 is:

$$\ln(w) = \alpha + \delta m(z, x) + \varepsilon \quad (19)$$

where $m(z, x) = |z - x|$.

The model is a simplification of reality and it abstracts from other wage determinants, both at the firm and the worker levels. If these wage determinants are correlated with mismatch, then omitting them from (19) is going to bias the mismatch estimate. Indeed, mismatch may be related to both firm's technology and workers' skills. Firms with worse technologies are likely to pay lower wages and to have more difficulty in searching for and hiring workers who match. At the same time, workers with worse skills also are likely to be paid lower wages and to end up being mismatched. The empirical exercise acknowledges that by running additional regressions with some covariates. Workers' skills (S) are measured by education, IQ score at high school, and high-school rank. Firms' technologies (T) are measured by firm size dummies and industry dummies. Hence, the augmented specification is:

$$\ln(w) = \alpha + \delta m(z, x) + \Pi S + \Lambda T + \mu \quad (20)$$

The model also establishes a well-defined relationship between workers' utility and mismatch:

$$u^*(m(z, x)) = (1 - \theta)[A(m(z, x)) - v(m(z, x))] \quad (21)$$

Moreover, according to Proposition 2, the effect of mismatch on utility is predicted to be negative. Hence, if the specification is:

$$u = \varsigma + \phi m(z, x) + \xi \quad (22)$$

a negative estimate of ϕ will be consistent with Proposition 2.

As a proxy for utility, I use job satisfaction⁶. Clark (2004) uses job satisfaction as a measure of the utility associated with working. He emphasizes that it is a good measure of how a worker feels about his or her job, often predicting workers' future behavior (quits, productivity, absenteeism), better than such objective variables as wage and hours of work in the case of quits.

The job satisfaction measure is constructed from the answer to the question: "All things considered, how satisfied are you with your job as a whole?": very satisfied, fairly satisfied, somewhat dissatisfied, very dissatisfied. The regressions are estimated as Ordered Probits. Again, as in the previous case, the empirical exercise also is performed adding some covariates:

$$u = \varsigma + \phi m(z, x) + \Theta S + \Psi T + \zeta \quad (23)$$

⁶ In empirical work, the use of job satisfaction has been rejected by economists as being useful or interesting for economic analysis (and it is still rejected by many economists today). Perhaps, as recognized by Freeman (1978), that is because it is a measure based on "what people say" rather than "what people do". Freeman notices that when using job satisfaction measures, complexities arise due to its dependency on psychological states. Nevertheless, he highlights that it contains useful information for predicting and understanding behavior.

Finally, to assess the role of mismatch on compensating wage differential estimates, I estimate the econometric specification defined in (4). The augmented version of (4) is given by

$$\ln(w) = \alpha + \beta z + \gamma x + \delta m(z, x) + \Pi S + \Lambda T + \tau \quad (24)$$

which I compare with standard wage equations that do not control either for workers' preferences or mismatch.

4.3. Descriptive Statistics

Table 7 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.

The vast majority of individuals are satisfied with their jobs: 90% (91%) of male (female) workers are fairly or very satisfied with their jobs. 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 8 shows the distribution of workers (by their preferences for routine and simple work) across jobs (by routinization). Among men, 42% of non-routine-preferring workers are mismatched into routinized jobs ($567/1359 \times 100$), while this percentage is 57 for women ($758/1331 \times 100$). 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).

Table 9 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.

5. Results

5.1. Model Estimates: the effect of mismatch in job routinization on wages and job satisfaction

Tables 10, 11, 12, and 13 present the results of Propositions 1 and 2. The model's prediction regarding the wage effect of mismatch is ambiguous. Table 10 shows that mismatch is negatively associated with hourly wages for men. According to my model, this suggests that the (negative) mismatch productivity effect dominates the (positive) mismatch compensating-wage-differential effect.

It is important to bear in mind that the model is a simplification of the real world and abstracts from other wage determinants. For this reason, columns (2)-(9) account for observed differences at the worker, firm, and industry levels that may be related to mismatch. The estimated effect of mismatch seems to be somewhere between -0.110 (column (1)) and -0.053 (column (6)).

However, column (6) may be problematic because of (over)controlling, since it includes completed education and its determinants at the same time, IQ at high school and high school rank. Note too that because I have neither variation in age nor education below high school, simultaneously adding education (indeed, adding education above high school) and industry dummies is likely to cause endogeneity problems. Furthermore, the average returns to education are known to be higher for women than for men, and this specification violates that (see column (6) in Table 11). For this reason, I prefer the specification in column (9), which leads to an estimate of -0.073 for the mismatch effect: on average, mismatched male workers earn 7.3% less than well-matched workers. In that model, I control (indirectly) for education through its determinants (IQ at high school and

high school rank). Note that in my sample, all individuals have at least high school education, so I do not control for education after high school, which indeed seems to be predicted by IQ at high school and high school rank. All specifications are consistent with this story, but with different intensity.

The results for women are reported in Table 11. They are qualitatively the same as for men, but the estimated mismatch effect is 60-85% of the mismatch effect for men, depending on the specification.

Overall, Tables 10 and 11 suggest that the mismatch productivity effect dominates the mismatch compensating-wage-differential effect (see Proposition 1).

My model also predicts that mismatch has a negative effect on utility. Tables 12 and 13, using job satisfaction as a proxy for utility, show that job satisfaction is negatively related to mismatch. Mismatched male and female workers report lower satisfaction levels. This relationship is robust to the addition of other covariates, which is evidence in favor of Proposition 2.

Finally, Tables 14 and 15 report the same regressions as in Tables 12 and 13 but conditioning on wages. Again, the results confirm the negative relationship between mismatch and job satisfaction.

Hence, the empirical evidence from Tables 12, 13, 14, and 15 is consistent with the predicted negative effect of mismatch on utility (see Proposition 2).

5.2. Implications for Compensating-Wage-Differentials Estimates: the effect of job routinization on wages

So far, the results are consistent with my model (Propositions 1 and 2). It is a simple model and its empirical predictions cannot be rejected by the data. In this subsection, I assess whether the model can shed light on the compensating wage differentials puzzle. In other words, I analyze the effect of accounting for mismatch on the association between job routinization and wages.

Recall that the crucial identifying assumption for the effect of mismatch on compensating-wage-differentials estimates is that the **compensating wage differential** applies to anyone working in the routinized sector (assuming that that sector has a shortage of workers in the absence of pay differentials), whether he prefers routine or non-routine work. By contrast, the **productivity effect** applies only to workers who are mismatched, that is, whose sectors do not match their preferences.

Tables 16 and 17 present the results on the effect of job routinization on wages for men and women, respectively. Column (1) in Table 16 shows that, on average, male workers in routinized jobs earn 10% 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% (see column (2)). Column (3) shows that routinized jobs on average pay 6% 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. Columns (4)-(6) show similar

qualitative results: male workers in routinized jobs earn 12% less than their counterparts in non-routinized jobs (see column (4)). This penalty decreases to 11% once I adjust for differences in preferences (see column (5)). Finally, once workers' preferences and mismatch are accounted for, this difference is reduced to 8% (see column (6)).

Table 17 reports similar results for women. Accounting for differences in preferences slightly decreases the job-routinization wage penalty, from 11% to 9% (columns (1) and (2)), or from 12% to 11% (columns (4) and (5)). However, adding mismatch into the model seems to be important: the effect of job routinization decreases from 9% to 4 % (columns (2) and (3)), or from 11% to 5% (columns (5) and (6)).

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) and job type (job routinization), which supports my model. 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. In the next section, I assess the robustness of my findings.

6. Robustness Checks

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

6.1. Omitted Variables

Although I have a rich set of observables that helps me to defend my identifying assumption, my regression contains two explanatory variables, worker's preferences and mismatch, which may well be endogenously determined and thus may compromise the interpretation of my estimates. I try to overcome this shortcoming by controlling for both tenure and adult cognition score, variables that previously were omitted.

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 can check the sensitivity of my results to the addition of tenure: keeping tenure constant, the effect of preferences on wages is obtained, net of the effect of tenure on preferences.

Further, in my model I assume that mismatch is random and reflects lower comparative advantage. That is to say, mismatch has a causal effect on wages. However, that assumption may well be too restrictive, given the age of my sample. While one can argue that for young workers mismatch is likely to be (at least in part) driven by the lack of information (in particular, the lack of labor market knowledge), for workers in their early fifties mismatch is more likely to reflect low ability, not a lack of labor market

knowledge. For this reason, I also control for a measure of adult cognition. If my new estimates do not substantially differ from my previous ones, then this would be evidence, albeit tentative at best, that the estimated mismatch effect does not capture the effect of unobserved ability, provided that my measure of adult cognition is a good proxy for unobserved ability⁷.

According to the results reported in Tables 18 and 19, my previous estimates are robust to the addition of these new controls. The new estimates of the effects of job routinization and mismatch are very similar, indeed almost identical, to my previous estimates in Tables 16 and 17.

6.2. Alternative Measures

I chose the threshold on the fraction of working time doing the same things over and over to define a job as routinized and the cutoff for classifying the worker as a routine-preferring or a non-routine-preferring one arbitrarily. In this subsection, I check the sensitivity of my estimates to such arbitrary decisions by using alternative criteria. 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 her 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.

⁷ My proxy for unobserved ability is the total cognition score reported in the WLS, measured in 1992. It is based on eight of the fourteen items from the Weschler Adult Intelligence Scale (WAIS). According to the WLS documents, the simplest items from the WAIS were eliminated because the general ability of the sample is high enough to cause little variation in response to those items. One example of the questions asked to compute the cognition score is: “*In what way are an orange and a banana alike?*”

In Tables 20 and 21 I provide new estimates, both using these alternative measures and accounting for differences in tenure and adult cognition. The new results are very similar to the ones obtained before. For men, workers in routinized jobs on average earn 9% less than their counterparts in non-routinized jobs (column (4) in Table 20). Column (5) shows that accounting for differences in preferences makes the wage penalty lower: 7%. Finally, adding mismatch into the model (column (6)) decreases the wage penalty even further: 4%. Note too that being mismatched is associated with a wage penalty of 8%. Similar qualitative results are shown for women in Table 21.

6.3. 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 22 and 23, which also control for tenure and adult cognition, are robust to outliers and very similar to my previous OLS estimates. In Table 22, column (4) shows that, at the median, male workers in routinized jobs earn 12% 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 (5)). Column (6) 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 23 shows similar results for women.

6.4. Other Issues

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. In this subsection, I exploit 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 most of the paper (see pages 19 and 20). 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 Tables 3 and 4). Workers' preference for routine is captured by several binary indicators: **Routine-Preferring Worker 1** (equal to 1 for workers who agree 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 disagree moderately or strongly with the previous statement, zero otherwise).

Tables 24 and 25 present the new estimates using these alternative measures of job routinization and workers' preferences. In these tables the omitted category is Routine-Preferring Worker 3. The new estimates are very similar to the earlier ones.

Finally, it is worth reporting the estimates from specification (17), the standard difference-in-difference estimator. Remember that the negative productivity effect of being mismatched corresponds to a positive interaction between a worker's taste for routinized work and the degree to which her observed job is routinized. For men, the

coefficient on the interaction term, using the models described in columns (3) and (6) from Table 16 are 0.086 (statistically significant at the 5% level) and 0.080 (statistically significant at the 1% level), respectively. For women, these coefficients are 0.151 and 0.142, both statistically significant at the 1% level.

To sum up, my results appear to be robust to a large variety of adjustments. Nonetheless, the next section addresses some caveats of my analysis, which are related mainly to the model and the dataset in the paper.

7. Caveats of my Analysis

The model offered in the paper is simple, easy to follow, and useful in showing the two opposite effects of mismatch. Although it is deliberately parsimonious, i.e., the only economic decision is about how to share the match surplus, the model helps us to think about the implications of mismatch when we look for compensating wage differentials. Moreover, because mismatch is taken as a given, the model does not restrict its possible determinants.

However, taking mismatch as a given has its own limitations. In order to evaluate the net gains from reducing or eliminating mismatch, we need to estimate the costs associated with such a policy. Unfortunately, because the determinants of mismatch are not defined, such a cost-benefit analysis cannot be performed⁸. Of course, it must also be

⁸ An upper bound on the gross gains from eliminating mismatch can be estimated easily. Using the model specified in column (6) from Table 16, I can estimate the expected (adjusted) wages for both well-matched and mismatched male workers. The expected hourly wage for well-matched workers is approximately US\$ 17, while the expected hourly wage for mismatched workers is approximately US\$ 15. Hence, the expected increase in the hourly wage rate for mismatched workers is US\$ 2. Since the percentage of mismatched workers is 38%, the estimated increase in the average hourly wage rate for males is US\$ 0.76 (76 cents of dollar), or approximately 4.5% of the average hourly wage rate for males in 1992. All of these quantities are expressed in US dollars of 1992.

recognized that this limitation avoids the possibility of drawing conclusions from dubious specifications.

My data is good enough to provide the first attempt at understanding the role of mismatch on compensating wage differentials, but it is not ideal. The sample under analysis covers workers in their early fifties, which makes it hard to believe that all observed mismatch is random. Second, mismatch can only be studied for the job routinization attribute. A richer dataset would contain longitudinal information on young workers and several job attributes, ideally measured at the firm level, and then matched perfectly with the workers' data on an individual basis. Such a dataset would be very useful for disentangling whether mismatch reflects lower comparative advantage or lower unobserved ability, and for assessing the implications of mismatch in multiple dimensions.

Finally, it should be noted that the absence of an instrument for mismatch prevents me from arguing that the associations I document are causal. However, the rich set of covariates I consider in the WLS (education, IQ at high school, high school rank, cognition score, preferences, tenure, firm size dummies, and industry dummies) help me to control to some extent for workers' skills and firm's technologies.

8. 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 argue that this discrepancy, or mismatch, has two different effects on wages. On the one hand, mismatched workers need to be compensated for performing a job (task) that does not match their type (preferences). This is the compensating wage differential effect: mismatch does increase wages. On the other hand, mismatched workers are less productive in performing a job (task) that does not match their type (preferences), since workers' preferences are likely correlated with comparative advantage. This is the productivity effect: mismatch decreases wages. Therefore, the effect of mismatch on wages is ambiguous. If mismatch is not accounted for, then the association between wages and job attributes may be picking up the correlation between job attributes, preferences, and mismatch.

I present a simple assignment model with Nash bargaining over wages in which randomly matched workers and firms bargain over the match surplus to decide the wage rate. This model predicts that mismatch is positively related to wages when it is simply a disamenity. However, once mismatch also reduces the match surplus, there is a negative effect on wages. Thus, in this last case, the effect of mismatch is ambiguous. In both cases, the effect on workers' utility and firms' profits is negative.

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 present several pieces of empirical evidence to support my model. First, mismatch is negatively related to wages, which is consistent with the negative mismatch productivity effect dominating the positive compensating wage differential effect. Second, I find that job satisfaction is negatively related to mismatch.

I also report the implications of omitting from wage regressions mismatch and workers' preferences in assessing the role of job routinization on wages (under the assumption that the compensating wage differential would apply to anyone working in the routinized sector but that the productivity effect would apply only to those workers who are mismatched). 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 points a new method of assessing the existence of compensating wage differentials. Clearly, as discussed in the section on caveats, 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.

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Figure 1: $E(\ln(w)|x, z)$

Worker Type	Job Type	Non-Routinized Job $z=0$	Routinized Job $z=1$	$E(\ln(w) x, z=1) - E(\ln(w) x, z=0)$
Non-Routine-Prefering Worker $x=0$		α	$\alpha + \beta + \delta$	$\beta + \delta$
Routine-Prefering Worker $x=1$		$\alpha + \gamma + \delta$	$\alpha + \beta + \gamma$	$\beta - \delta$

Figure 2: $E(\ln(w)|x, z)$

Worker Type	Job Type	Non-Routinized Job $z=0$	Routinized Job $z=1$	$E(\ln(w) x, z=1) - E(\ln(w) x, z=0)$
Non-Routine-Prefering Worker $x=0$		α^*	$\alpha^* + \beta^*$	β^*
Routine-Prefering Worker $x=1$		$\alpha^* + \gamma^*$	$\alpha^* + \beta^* + \gamma^* + \delta^*$	$\beta^* + \delta^*$
$E(\ln(w) x=1, z) - E(\ln(w) x=0, z)$		γ^*	$\gamma^* + \delta^*$	δ^*

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: 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 Operations	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
Precise 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, and Related Occupations	0.73	0.90

Source: Author's calculations.

Table 3: Job routinization and wages by workers' preferences.									
OLS estimates for men. Dependent variable: ln(hourly wage)									
Job Routinization = fraction of weekly worked hours doing the same things over and over									
	Workers' Preferences			Workers' Preferences			Workers' Preferences		
	Routine	Non-Routine	Non-Routine	Routine	Non-Routine	Non-Routine	Routine	Non-Routine	Non-Routine
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	
Job Routinization	-0.000 (0.051)	-0.232 (0.025)	0.023 (0.052)	-0.161 (0.023)	0.023 (0.052)	-0.147 (0.024)	0.002 (0.055)	-0.151 (0.025)	
Completed Years of Education	--	--	0.051 (0.013)	0.051 (0.004)	0.043 (0.013)	0.045 (0.004)	0.041 (0.013)	0.045 (0.004)	
<u>Workers' skills</u>									
IQ Measured at High School	--	--	--	--	0.002 (0.001)	0.003 (0.001)	0.002 (0.002)	0.003 (0.001)	
High School Rank	--	--	--	--	--	--	0.001 (0.001)	0.000 (0.000)	
<u>Firm's technology</u>									
Firm Size dummies	NO	NO	NO	NO	NO	NO	NO	NO	NO
Industry Type dummies	NO	NO	NO	NO	NO	NO	NO	NO	NO
R ²	0.00	0.06	0.05	0.17	0.06	0.18	0.06	0.19	
Sample Size	297	1,359	297	1,359	297	1,359	273	1,261	
Note: Heteroskedasticity robust standard errors are reported in parentheses.									

Table 3 (continued)												
	Workers' Preferences			Workers' Preferences			Workers' Preferences			Workers' Preferences		
	Routine			Non-Routine			Routine			Non-Routine		
	(9)	(10)	(11)	(12)	(13)	(14)	(15)	(16)				
Job Routinization	-0.012 (0.055)	-0.143 (0.024)	-0.016 (0.056)	-0.131 (0.024)	-0.024 (0.055)	-0.179 (0.025)	-0.022 (0.056)	-0.163 (0.025)				
Completed Years of Education	0.040 (0.014)	0.045 (0.004)	0.055 (0.016)	0.055 (0.005)	--	--	--	--				
<u>Workers' skills</u>												
IQ Measured at High School	0.002 (0.002)	0.003 (0.001)	0.002 (0.002)	0.003 (0.001)	0.003 (0.002)	0.004 (0.001)	0.003 (0.002)	0.004 (0.001)				
High School Rank	0.000 (0.001)	0.000 (0.000)	-0.000 (0.001)	0.000 (0.000)	0.001 (0.001)	0.001 (0.000)	0.001 (0.001)	0.001 (0.000)				
<u>Firm's technology</u>												
Firm Size dummies	YES	YES	YES	YES	YES	YES	YES	YES				
Industry Type dummies	NO	NO	YES	YES	NO	NO	YES	YES				
R ²	0.10	0.25	0.21	0.28	0.08	0.18	0.17	0.21				
Sample Size	273	1,273	273	1,255	273	1,257	273	1,255				

Table 4: Job routinization and wages by workers' preferences. OLS estimates for women. Dependent variable: ln(hourly wage) Job Routinization = fraction of weekly worked hours doing the same things over and over									
	Workers' Preferences			Workers' Preferences			Workers' Preferences		
	Non-Routine		Routine	Non-Routine		Routine	Non-Routine		Routine
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	
Job Routinization	-0.076 (0.054)	-0.264 (0.026)	-0.038 (0.055)	-0.190 (0.027)	-0.021 (0.055)	-0.159 (0.027)	-0.012 (0.057)	-0.149 (0.028)	
Completed Years of Education	--	--	0.071 (0.018)	0.050 (0.006)	0.065 (0.018)	0.039 (0.006)	0.066 (0.019)	0.039 (0.006)	
<u>Workers' skills</u>									
IQ Measured at High School	--	--	--	--	0.003 (0.001)	0.005 (0.001)	0.004 (0.002)	0.005 (0.001)	
High School Rank	--	--	--	--	--	--	-0.001 (0.001)	0.001 (0.001)	
<u>Firm's technology</u>									
Firm Size dummies	NO	NO	NO	NO	NO	NO	NO	NO	NO
Industry Type dummies	NO	NO	NO	NO	NO	NO	NO	NO	NO
R ²	0.01	0.07	0.06	0.13	0.07	0.16	0.07	0.16	
Sample Size	412	1,331	412	1,331	412	1,331	384	1,247	
Note: Heteroskedasticity robust standard errors are reported in parentheses.									

Table 4 (continued)												
	Workers' Preferences			Workers' Preferences			Workers' Preferences			Workers' Preferences		
	Routine			Non-Routine			Routine			Non-Routine		
	(9)	(10)	(11)	(12)	(13)	(14)	(15)	(16)	(17)	(18)	(19)	(20)
Job Routinization	-0.063 (0.053)	-0.158 (0.027)	-0.048 (0.053)	-0.136 (0.026)	-0.087 (0.053)	-0.202 (0.027)	-0.071 (0.052)	-0.168 (0.026)				
Completed Years of Education	0.071 (0.019)	0.040 (0.006)	0.078 (0.019)	0.034 (0.006)	--	--	--	--				
<u>Workers' skills</u>												
IQ Measured at High School	0.004 (0.002)	0.004 (0.001)	0.004 (0.002)	0.005 (0.001)	0.004 (0.002)	0.005 (0.001)	0.004 (0.002)	0.006 (0.001)				
High School Rank	-0.000 (0.001)	0.001 (0.000)	-0.000 (0.001)	0.001 (0.001)	0.000 (0.001)	0.001 (0.000)	0.001 (0.001)	0.001 (0.000)				
<u>Firm's technology</u>												
Firm Size dummies	YES	YES	YES	YES	YES	YES	YES	YES				
Industry Type dummies	NO	NO	YES	YES	NO	NO	YES	YES				
R ²	0.22	0.25	0.29	0.31	0.17	0.22	0.24	0.29				
Sample Size	381	1,241	381	1,241	381	1,241	381	1,241				

Table 5: Job routinization and wages by workers' preferences.								
OLS estimates for men. Dependent variable: ln(hourly wage)								
Job Routinization = 1 if the fraction of weekly worked hours doing the same things over and over is higher than 0.5, = 0 otherwise								
	Workers' Preferences		Workers' Preferences		Workers' Preferences		Workers' Preferences	
	Routine	Non-Routine	Routine	Non-Routine	Routine	Non-Routine	Routine	Non-Routine
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Job Routinization	-0.024 (0.040)	-0.160 (0.019)	-0.014 (0.039)	-0.111 (0.018)	-0.016 (0.039)	-0.101 (0.018)	-0.034 (0.042)	-0.104 (0.019)
Completed Years of Education	--	--	0.050 (0.013)	0.052 (0.004)	0.042 (0.013)	0.045 (0.004)	0.041 (0.013)	0.046 (0.004)
<u>Workers' skills</u>								
IQ Measured at High School	--	--	--	--	0.002 (0.001)	0.003 (0.001)	0.002 (0.002)	0.003 (0.001)
High School Rank	--	--	--	--	--	--	0.001 (0.001)	0.000 (0.000)
<u>Firm's technology</u>								
Firm Size dummies	NO	NO	NO	NO	NO	NO	NO	NO
Industry Type dummies	NO	NO	NO	NO	NO	NO	NO	NO
R ²	0.00	0.05	0.05	0.17	0.06	0.18	0.07	0.19
Sample Size	297	1,359	297	1,359	297	1,359	273	1,261

Note: Heteroskedasticity robust standard errors are reported in parentheses.

Table 5 (continued)											
	Workers' Preferences			Workers' Preferences			Workers' Preferences			Workers' Preferences	
	Routine		Non-Routine	Routine		Non-Routine	Routine		Non-Routine	Routine	
	(9)	(10)	(11)	(12)	(13)	(14)	(15)	(16)			
Job Routinization	-0.042 (0.042)	-0.100 (0.018)	-0.037 (0.041)	-0.092 (0.018)	-0.046 (0.042)	-0.124 (0.019)	-0.037 (0.042)	-0.115 (0.019)			
Completed Years of Education	0.040 (0.014)	0.046 (0.004)	0.055 (0.016)	0.055 (0.005)	--	--	--	--			
<u>Workers' skills</u>											
IQ Measured at High School	0.002 (0.002)	0.003 (0.001)	0.002 (0.002)	0.003 (0.001)	0.003 (0.002)	0.005 (0.001)	0.003 (0.002)	0.005 (0.001)			
High School Rank	0.000 (0.001)	0.000 (0.000)	-0.000 (0.001)	0.000 (0.000)	0.001 (0.001)	0.001 (0.000)	0.001 (0.001)	0.001 (0.000)			
<u>Firm's technology</u>											
Firm Size dummies	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES
Industry Type dummies	NO	NO	YES	YES	NO	NO	YES	NO	YES	YES	YES
R ²	0.11	0.24	0.21	0.28	0.08	0.17	0.17	0.21			
Sample Size	273	1,257	273	1,255	273	1,257	273	1,255			

Table 6: Job routinization and wages by workers' preferences.									
OLS estimates for women. Dependent variable: ln(hourly wage)									
Job Routinization = 1 if the fraction of weekly worked hours doing the same things over and over is higher than 0.5, = 0 otherwise									
	Workers' Preferences			Workers' Preferences			Workers' Preferences		
	Routine	Non-Routine	Routine	Non-Routine	Routine	Non-Routine	Routine	Non-Routine	Routine
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	
Job Routinization	0.008 (0.042)	-0.187 (0.020)	0.021 (0.043)	-0.135 (0.020)	0.033 (0.043)	-0.112 (0.020)	0.042 (0.044)	-0.108 (0.021)	
Completed Years of Education	--	--	0.073 (0.017)	0.051 (0.006)	0.066 (0.018)	0.041 (0.006)	0.066 (0.018)	0.040 (0.006)	
<u>Workers' skills</u>									
IQ Measured at High School	--	--	--	--	0.003 (0.001)	0.005 (0.001)	0.004 (0.002)	0.005 (0.001)	
High School Rank	--	--	--	--	--	--	-0.000 (0.001)	0.001 (0.001)	
<u>Firm's technology</u>									
Firm Size dummies	NO	NO	NO	NO	NO	NO	NO	NO	NO
Industry Type dummies	NO	NO	NO	NO	NO	NO	NO	NO	NO
R ²	0.00	0.06	0.06	0.12	0.07	0.16	0.07	0.16	
Sample Size	412	1,331	412	1,331	412	1,331	384	1,247	

Note: Heteroskedasticity robust standard errors are reported in parentheses.

Table 6 (continued)											
	Workers' Preferences			Workers' Preferences			Workers' Preferences			Workers' Preferences	
	Routine		Non-Routine	Routine		Non-Routine	Routine		Non-Routine	Routine	
	(9)	(10)	(11)	(12)	(13)	(14)	(15)	(16)			
Job Routinization	0.003 (0.041)	-0.112 (0.020)	-0.002 (0.042)	-0.096 (0.020)	0.004 (0.042)	-0.143 (0.020)	0.003 (0.042)	-0.118 (0.019)			
Completed Years of Education	0.073 (0.019)	0.041 (0.006)	0.079 (0.019)	0.035 (0.006)	--	--	--	--			
<u>Workers' skills</u>											
IQ Measured at High School	0.004 (0.002)	0.004 (0.001)	0.004 (0.002)	0.005 (0.001)	0.004 (0.002)	0.005 (0.001)	0.004 (0.002)	0.006 (0.001)			
High School Rank	-0.000 (0.001)	0.001 (0.000)	-0.000 (0.001)	0.001 (0.000)	0.001 (0.001)	0.001 (0.000)	0.001 (0.001)	0.001 (0.000)			
<u>Firm's technology</u>											
Firm Size dummies	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES
Industry Type dummies	NO	NO	YES	YES	NO	NO	YES	YES	NO	YES	YES
R ²	0.22	0.25	0.29	0.31	0.16	0.22	0.23	0.29			
Sample Size	381	1,241	381	1,241	381	1,241	381	1,241			

Table 7: 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 7: (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
Job Satisfaction						
Very satisfied	812	0.49	--	919	0.52	--
Fairly satisfied	703	0.42	--	661	0.38	--
Somewhat dissatisfied	117	0.07	--	139	0.08	--
Very dissatisfied	31	0.02	--	28	0.02	--
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 8: Distribution of workers across jobs, 1992-3.

(Number of observations)	$z = 0$	$z = 1$
Male		
$x = 0$	48% (792)	34% (567)
$x = 1$	4% (69)	14% (228)
Female		
$x = 0$	33% (573)	43% (758)
$x = 1$	4% (63)	20% (349)

Note: Author's calculations.

Table 9: Average hourly wages by worker-job type, US\$ 1992-3.

(Number of observations)	$z = 0$	$z = 1$
Male		
$x = 0$	18.4 (792)	15.7 (567)
$x = 1$	14.3 (69)	14.0 (228)
Female		
$x = 0$	11.8 (573)	9.7 (758)
$x = 1$	8.4 (63)	8.5 (349)

Note: Author's calculations.

Table 10: Mismatch and wages. OLS estimates for men. Dependent variable: ln(hourly wage)									
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
Mismatch	-0.110 (0.017)	-0.073 (0.016)	-0.067 (0.016)	-0.066 (0.017)	-0.062 (0.016)	-0.053 (0.016)	-0.084 (0.017)	-0.080 (0.017)	-0.073 (0.017)
Completed Years of Education	--	0.059 (0.004)	0.049 (0.004)	0.049 (0.004)	0.049 (0.004)	0.058 (0.005)	--	--	--
<u>Workers' skills</u>									
IQ Measured at High School	--	--	0.004 (0.001)	0.003 (0.001)	0.004 (0.001)	0.004 (0.001)	0.005 (0.001)	0.005 (0.001)	0.005 (0.001)
High School Rank	--	--	--	0.001 (0.001)	0.000 (0.000)	0.000 (0.000)	0.002 (0.000)	0.002 (0.000)	0.002 (0.000)
<u>Firm's technology</u>									
Firm Size dummies	NO	NO	NO	NO	YES	YES	NO	YES	YES
Industry Type dummies	NO	NO	NO	NO	NO	YES	NO	NO	YES
R ²	0.02	0.16	0.18	0.19	0.24	0.27	0.12	0.16	0.19
Sample Size	1,656	1,656	1,656	1,534	1,530	1,528	1,534	1,530	1,528

Note: Heteroskedasticity robust standard errors are reported in parentheses.

Table 11: Mismatch and wages. OLS estimates for women. Dependent variable: ln(hourly wage)									
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
Mismatch	-0.079 (0.018)	-0.042 (0.017)	-0.043 (0.017)	-0.045 (0.017)	-0.040 (0.017)	-0.032 (0.016)	-0.071 (0.017)	-0.065 (0.017)	-0.052 (0.016)
Completed Years of Education	--	0.067 (0.005)	0.051 (0.006)	0.049 (0.006)	0.051 (0.006)	0.046 (0.006)	--	--	--
<u>Workers' skills</u>									
IQ Measured at High School	--	--	0.006 (0.001)	0.006 (0.001)	0.005 (0.001)	0.005 (0.001)	0.007 (0.001)	0.007 (0.001)	0.007 (0.001)
High School Rank	--	--	--	0.001 (0.000)	0.001 (0.000)	0.001 (0.000)	0.001 (0.000)	0.002 (0.000)	0.001 (0.000)
<u>Firm's technology</u>									
Firm Size dummies	NO	NO	NO	NO	YES	YES	NO	YES	YES
Industry Type dummies	NO	NO	NO	NO	NO	YES	NO	NO	YES
R ²	0.01	0.11	0.15	0.16	0.25	0.30	0.12	0.20	0.27
Sample Size	1,743	1,743	1,743	1,631	1,622	1,622	1,631	1,622	1,622

Note: Heteroskedasticity robust standard errors are reported in parentheses.

Table 12: Mismatch and job satisfaction. Ordered Probit estimates for men. Dependent variable: 1 (very dissatisfied), 2 (somewhat dissatisfied), 3 (fairly satisfied), 4 (very satisfied)									
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
Mismatch	-0.187 (0.058)	-0.188 (0.058)	-0.196 (0.059)	-0.220 (0.061)	-0.217 (0.061)	-0.214 (0.062)	-0.225 (0.061)	-0.223 (0.061)	-0.217 (0.062)
Completed Years of Education	--	-0.003 (0.013)	0.009 (0.014)	0.016 (0.016)	0.016 (0.016)	0.006 (0.018)	--	--	--
<u>Workers' skills</u>									
IQ Measured at High School	--	--	-0.005 (0.002)	-0.004 (0.003)	-0.005 (0.003)	-0.005 (0.003)	-0.004 (0.003)	-0.004 (0.003)	-0.005 (0.003)
High School Rank	--	--	--	-0.001 (0.000)	-0.001 (0.000)	-0.001 (0.001)	-0.000 (0.001)	-0.000 (0.001)	-0.000 (0.001)
<u>Firm's technology</u>									
Firm Size dummies	NO	NO	NO	NO	YES	YES	NO	YES	YES
Industry Type dummies	NO	NO	NO	NO	NO	YES	NO	NO	YES
Pseudo-R ²	0.00	0.00	0.00	0.01	0.01	0.01	0.01	0.01	0.01
Sample Size	1,654	1,654	1,654	1,532	1,528	1,526	1,532	1,528	1,526
Note: Heteroskedasticity robust standard errors are reported in parentheses.									

Table 13: Mismatch and job satisfaction. Ordered Probit estimates for women. Dependent variable: 1 (very dissatisfied), 2 (somewhat dissatisfied), 3 (fairly satisfied), 4 (very satisfied)									
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
Mismatch	-0.245 (0.056)	-0.257 (0.057)	-0.257 (0.057)	-0.276 (0.059)	-0.277 (0.059)	-0.273 (0.059)	-0.267 (0.058)	-0.268 (0.058)	-0.259 (0.058)
Completed Years of Education	--	-0.023 (0.016)	-0.023 (0.017)	-0.019 (0.018)	-0.021 (0.018)	-0.033 (0.019)	--	--	--
<u>Workers' skills</u>									
IQ Measured at High School	--	--	0.000 (0.002)	0.001 (0.003)	0.001 (0.003)	0.001 (0.003)	0.001 (0.003)	0.001 (0.003)	0.000 (0.003)
High School Rank	--	--	--	-0.001 (0.001)	-0.001 (0.001)	-0.001 (0.001)	-0.001 (0.001)	-0.001 (0.001)	-0.001 (0.001)
<u>Firm's technology</u>									
Firm Size dummies	NO	NO	NO	NO	YES	YES	NO	YES	YES
Industry Type dummies	NO	NO	NO	NO	NO	YES	NO	NO	YES
Pseudo-R ²	0.01	0.01	0.01	0.01	0.01	0.02	0.01	0.01	0.01
Sample Size	1,742	1,742	1,742	1,630	1,621	1,621	1,630	1,621	1,621
Note: Heteroskedasticity robust standard errors are reported in parentheses.									

Table 14: Mismatch and compensating wage differentials.
OLS estimates for men.
Dependent variable: ln(hourly wage)

	(1)	(2)	(3)	(4)	(5)	(6)
Job Routinization	-0.100 (0.016)	-0.090 (0.016)	-0.059 (0.021)	-0.122 (0.017)	-0.107 (0.017)	-0.078 (0.022)
Routine-Preferring Worker	--	-0.075 (0.020)	-0.095 (0.022)	--	-0.096 (0.021)	-0.115 (0.023)
Mismatch	--	--	-0.043 (0.022)	--	--	-0.040 (0.022)
Completed Years of Education	0.047 (0.004)	0.045 (0.004)	0.045 (0.004)	--	--	--
<u>Workers' skills</u>						
IQ Measured at High School	0.003 (0.001)	0.003 (0.001)	0.003 (0.001)	0.005 (0.001)	0.004 (0.001)	0.004 (0.001)
High School Rank	--	--	--	0.001 (0.000)	0.001 (0.000)	0.001 (0.000)
<u>Firm's technology</u>						
Firm Size Dummies	NO	NO	NO	YES	YES	YES
Industry Type Dummies	NO	NO	NO	YES	YES	YES
R ²	0.19	0.20	0.20	0.21	0.22	0.22
Sample Size	1,665	1,656	1,656	1,537	1,528	1,528

Notes: Heteroskedasticity robust standard errors are reported in parentheses.

Table 15: Mismatch and compensating wage differentials.**OLS estimates for women.****Dependent variable: ln(hourly wage)**

	(1)	(2)	(3)	(4)	(5)	(6)
Job Routinization	-0.105 (0.018)	-0.090 (0.018)	-0.037 (0.024)	-0.120 (0.018)	-0.105 (0.018)	-0.054 (0.023)
Routine-Preferring Worker	--	-0.109 (0.019)	-0.156 (0.024)	--	-0.109 (0.019)	-0.153 (0.023)
Mismatch	--	--	-0.075 (0.023)	--	--	-0.072 (0.022)
Completed Years of Education	0.046 (0.006)	0.045 (0.006)	0.044 (0.006)	--	--	--
<u>Workers' skills</u>						
IQ Measured at High School	0.006 (0.001)	0.005 (0.001)	0.005 (0.001)	0.006 (0.001)	0.005 (0.001)	0.005 (0.001)
High School Rank	--	--	--	0.001 (0.000)	0.001 (0.000)	0.001 (0.000)
<u>Firm's technology</u>						
Firm Size Dummies	NO	NO	NO	YES	YES	YES
Industry Type Dummies	NO	NO	NO	YES	YES	YES
R ²	0.17	0.18	0.19	0.29	0.30	0.30
Sample Size	1,748	1,743	1,743	1,627	1,622	1,622

Notes: Heteroskedasticity robust standard errors are reported in parentheses.

APPENDIX

**Table 1A: Mismatch and job satisfaction, wage-adjusted estimates.
Ordered Probit estimates for men.**

Dependent variable: 1 (very dissatisfied), 2 (somewhat dissatisfied), 3 (fairly satisfied), 4 (very satisfied)	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
Mismatch	-0.151 (0.058)	-0.161 (0.059)	-0.169 (0.059)	-0.192 (0.061)	-0.192 (0.062)	-0.194 (0.062)	-0.191 (0.061)	-0.191 (0.061)	-0.190 (0.062)
Ln(hourly wage)	0.339 (0.084)	0.404 (0.090)	0.443 (0.092)	0.448 (0.098)	0.453 (0.102)	0.429 (0.105)	0.438 (0.094)	0.441 (0.097)	0.397 (0.100)
Completed Years of Education	--	-0.027 (0.014)	-0.013 (0.015)	-0.006 (0.016)	-0.007 (0.017)	-0.019 (0.019)	--	--	--
<u>Workers' skills</u>									
IQ Measured at High School	--	--	-0.006 (0.002)	-0.006 (0.003)	-0.006 (0.003)	-0.006 (0.003)	-0.006 (0.003)	-0.006 (0.003)	-0.007 (0.003)
High School Rank	--	--	--	-0.001 (0.001)	-0.001 (0.001)	-0.001 (0.001)	-0.001 (0.001)	-0.001 (0.001)	-0.001 (0.001)
<u>Firm's technology</u>									
Firm Size dummies	NO	NO	NO	NO	YES	YES	NO	YES	YES
Industry Type dummies	NO	NO	NO	NO	NO	YES	NO	NO	YES
Pseudo-R ²	0.01	0.01	0.01	0.01	0.01	0.01	0.01	0.01	0.02
Sample Size	1,654	1,654	1,654	1,532	1,528	1,526	1,532	1,528	1,526

Note: Heteroskedasticity robust standard errors are reported in parentheses.

Table 2A: Mismatch and job satisfaction, wage-adjusted estimates. Ordered Probit estimates for women. Dependent variable: 1 (very dissatisfied), 2 (somewhat dissatisfied), 3 (fairly satisfied), 4 (very satisfied)									
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
Mismatch	-0.231 (0.056)	-0.247 (0.057)	-0.246 (0.057)	-0.265 (0.059)	-0.264 (0.059)	-0.264 (0.059)	-0.252 (0.058)	-0.250 (0.058)	-0.247 (0.058)
Ln(hourly wage)	0.189 (0.074)	0.246 (0.078)	0.259 (0.080)	0.253 (0.083)	0.345 (0.090)	0.303 (0.094)	0.222 (0.081)	0.301 (0.087)	0.255 (0.091)
Completed Years of Education	--	-0.040 (0.017)	-0.037 (0.018)	-0.031 (0.018)	-0.039 (0.019)	-0.047 (0.019)	--	--	--
<u>Workers' skills</u>									
IQ Measured at High School	--	--	-0.002 (0.002)	-0.001 (0.003)	-0.001 (0.003)	-0.001 (0.003)	-0.001 (0.003)	-0.002 (0.003)	-0.002 (0.003)
High School Rank	--	--	--	-0.001 (0.001)	-0.001 (0.001)	-0.001 (0.001)	-0.001 (0.001)	-0.001 (0.001)	-0.001 (0.001)
<u>Firm's technology</u>									
Firm Size dummies	NO	NO	NO	NO	YES	YES	NO	YES	YES
Industry Type dummies	NO	NO	NO	NO	NO	YES	NO	NO	YES
Pseudo-R ²	0.01	0.01	0.01	0.01	0.02	0.02	0.01	0.01	0.02
Sample Size	1,742	1,742	1,742	1,630	1,621	1,621	1,630	1,621	1,621
Note: Heteroskedasticity robust standard errors are reported in parentheses.									

Table 3A: Mismatch and compensating wage differentials.**Additional covariates.****OLS estimates for men.****Dependent variable: ln(hourly wage)**

	(1)	(2)	(3)	(4)	(5)	(6)
Job Routinization	-0.103 (0.015)	-0.090 (0.015)	-0.060 (0.021)	-0.122 (0.016)	-0.107 (0.017)	-0.074 (0.022)
Routine-Preferring Worker	--	-0.083 (0.019)	-0.102 (0.021)	--	-0.093 (0.020)	-0.115 (0.022)
Mismatch	--	--	-0.043 (0.021)	--	--	-0.046 (0.021)
Completed Years of Education	0.049 (0.004)	0.048 (0.004)	0.048 (0.004)	--	--	--
<u>Workers' skills</u>						
IQ Measured at High School	0.003 (0.001)	0.003 (0.001)	0.003 (0.001)	0.004 (0.001)	0.004 (0.001)	0.004 (0.001)
High School Rank	--	--	--	0.001 (0.000)	0.001 (0.000)	0.001 (0.000)
<u>Firm's technology</u>						
Firm Size Dummies	NO	NO	NO	YES	YES	YES
Industry Type Dummies	NO	NO	NO	YES	YES	YES
<u>Additional covariates</u>						
Tenure	0.009 (0.001)	0.009 (0.001)	0.009 (0.001)	0.006 (0.001)	0.006 (0.001)	0.006 (0.001)
Adult Cognition Score	0.006 (0.003)	0.005 (0.003)	0.005 (0.003)	0.011 (0.003)	0.010 (0.003)	0.010 (0.003)
R ²	0.27	0.28	0.28	0.25	0.26	0.26
Sample Size	1,647	1,644	1,644	1,521	1,518	1,518

Notes: Heteroskedasticity robust standard errors are reported in parentheses.

Table 4A: Mismatch and compensating wage differentials.**Additional covariates.****OLS estimates for women.****Dependent variable: ln(hourly wage)**

	(1)	(2)	(3)	(4)	(5)	(6)
Job Routinization	−0.102 (0.017)	−0.085 (0.017)	−0.039 (0.021)	−0.119 (0.017)	−0.103 (0.017)	−0.053 (0.021)
Routine-Preferring Worker	--	−0.110 (0.017)	−0.151 (0.021)	--	−0.115 (0.018)	−0.157 (0.021)
Mismatch	--	--	−0.066 (0.020)	--	--	−0.069 (0.020)
Completed Years of Education	0.047 (0.005)	0.045 (0.005)	0.044 (0.005)	--	--	--
<u>Workers' skills</u>						
IQ Measured at High School	0.005 (0.001)	0.005 (0.001)	0.005 (0.001)	0.006 (0.001)	0.005 (0.001)	0.005 (0.001)
High School Rank	--	--	--	0.001 (0.000)	0.000 (0.000)	0.000 (0.000)
<u>Firm's technology</u>						
Firm Size Dummies	NO	NO	NO	YES	YES	YES
Industry Type Dummies	NO	NO	NO	YES	YES	YES
<u>Additional covariates</u>						
Tenure	0.015 (0.001)	0.015 (0.001)	0.015 (0.001)	0.012 (0.001)	0.012 (0.001)	0.012 (0.001)
Adult Cognition Score	0.004 (0.003)	0.004 (0.003)	0.004 (0.003)	0.009 (0.003)	0.009 (0.003)	0.009 (0.003)
R ²	0.30	0.32	0.32	0.37	0.38	0.39
Sample Size	1,735	1,733	1,733	1,614	1,612	1,612

Notes: Heteroskedasticity robust standard errors are reported in parentheses.

Table 5A: Mismatch and compensating wage differentials.
Additional covariates and alternative measures I.
OLS estimates for men.
Dependent variable: ln(hourly wage)

	(1)	(2)	(3)	(4)	(5)	(6)
Job Routinization	−0.069 (0.017)	−0.054 (0.017)	−0.028 (0.018)	−0.089 (0.018)	−0.071 (0.019)	−0.040 (0.020)
Routine-Preferring Worker	--	−0.090 (0.019)	−0.075 (0.019)	--	−0.104 (0.020)	−0.086 (0.020)
Mismatch	--	--	−0.067 (0.018)	--	--	−0.077 (0.019)
Completed Years of Education	0.050 (0.004)	0.049 (0.004)	0.049 (0.004)	--	--	--
<u>Workers' skills</u>						
IQ Measured at High School	0.003 (0.001)	0.003 (0.001)	0.003 (0.001)	0.004 (0.001)	0.004 (0.001)	0.004 (0.001)
High School Rank	--	--	--	0.001 (0.000)	0.001 (0.000)	0.001 (0.000)
<u>Firm's technology</u>						
Firm Size Dummies	NO	NO	NO	YES	YES	YES
Industry Type Dummies	NO	NO	NO	YES	YES	YES
<u>Additional covariates</u>						
Tenure	0.009 (0.001)	0.009 (0.001)	0.009 (0.001)	0.006 (0.001)	0.006 (0.001)	0.006 (0.001)
Adult Cognition Score	0.007 (0.003)	0.005 (0.003)	0.006 (0.003)	0.012 (0.003)	0.010 (0.003)	0.010 (0.003)
R ²	0.25	0.27	0.27	0.24	0.25	0.26
Sample Size	1,647	1,644	1,644	1,521	1,518	1,518

Notes: Heteroskedasticity robust standard errors are reported in parentheses.

Table 6A: Mismatch and compensating wage differentials.
Additional covariates and alternative measures I.
OLS estimates for women.
Dependent variable: ln(hourly wage)

	(1)	(2)	(3)	(4)	(5)	(6)
Job Routinization	-0.089 (0.016)	-0.072 (0.016)	-0.056 (0.017)	-0.103 (0.017)	-0.087 (0.016)	-0.071 (0.017)
Routine-Preferring Worker	--	-0.112 (0.017)	-0.110 (0.017)	--	-0.118 (0.017)	-0.117 (0.017)
Mismatch	--	--	-0.037 (0.017)	--	--	-0.035 (0.017)
Completed Years of Education	0.049 (0.005)	0.048 (0.005)	0.047 (0.005)	--	--	--
<u>Workers' skills</u>						
IQ Measured at High School	0.006 (0.001)	0.005 (0.001)	0.005 (0.001)	0.006 (0.001)	0.006 (0.001)	0.005 (0.001)
High School Rank	--	--	--	0.001 (0.000)	0.000 (0.000)	0.000 (0.000)
<u>Firm's technology</u>						
Firm Size Dummies	NO	NO	NO	YES	YES	YES
Industry Type Dummies	NO	NO	NO	YES	YES	YES
<u>Additional covariates</u>						
Tenure	0.015 (0.001)	0.015 (0.001)	0.015 (0.001)	0.012 (0.001)	0.012 (0.001)	0.012 (0.001)
Adult Cognition Score	0.004 (0.003)	0.004 (0.003)	0.004 (0.003)	0.009 (0.003)	0.009 (0.003)	0.009 (0.003)
R ²	0.30	0.31	0.32	0.36	0.38	0.38
Sample Size	1,735	1,733	1,733	1,614	1,612	1,612

Notes: Heteroskedasticity robust standard errors are reported in parentheses.

Table 7A: Mismatch and compensating wage differentials.**Additional covariates.****Quantile Median estimates for men.****Dependent variable: ln(hourly wage)**

	(1)	(2)	(3)	(4)	(5)	(6)
Job Routinization	-0.103 (0.020)	-0.076 (0.021)	-0.026 (0.028)	-0.115 (0.021)	-0.085 (0.021)	-0.052 (0.027)
Routine-Preferring Worker	--	-0.078 (0.022)	-0.126 (0.028)	--	-0.084 (0.025)	-0.111 (0.027)
Mismatch	--	--	-0.072 (0.028)	--	--	-0.056 (0.027)
Completed Years of Education	0.054 (0.005)	0.053 (0.005)	0.054 (0.005)	--	--	--
<u>Workers' skills</u>						
IQ Measured at High School	0.003 (0.001)	0.003 (0.001)	0.003 (0.001)	0.003 (0.001)	0.003 (0.001)	0.003 (0.001)
High School Rank	--	--	--	0.002 (0.001)	0.001 (0.000)	0.001 (0.000)
<u>Firm's technology</u>						
Firm Size Dummies	NO	NO	NO	YES	YES	YES
Industry Type Dummies	NO	NO	NO	YES	YES	YES
<u>Additional covariates</u>						
Tenure	0.008 (0.001)	0.009 (0.001)	0.008 (0.001)	0.005 (0.001)	0.006 (0.001)	0.006 (0.001)
Adult Cognition Score	0.008 (0.004)	0.007 (0.004)	0.006 (0.004)	0.014 (0.004)	0.014 (0.004)	0.015 (0.004)
Pseudo-R ²	0.16	0.17	0.17	0.16	0.16	0.17
Sample Size	1,647	1,644	1,644	1,521	1,518	1,518

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

Table 8A: Mismatch and compensating wage differentials.**Additional covariates.****Quantile Median estimates for women.****Dependent variable: ln(hourly wage)**

	(1)	(2)	(3)	(4)	(5)	(6)
Job Routinization	−0.101 (0.023)	−0.083 (0.022)	−0.058 (0.025)	−0.119 (0.023)	−0.117 (0.023)	−0.065 (0.026)
Routine-Preferring Worker	--	−0.132 (0.021)	−0.152 (0.026)	--	−0.103 (0.024)	−0.151 (0.027)
Mismatch	--	--	−0.057 (0.024)	--	--	−0.086 (0.017)
Completed Years of Education	0.065 (0.007)	0.063 (0.007)	0.065 (0.007)	--	--	--
<u>Workers' skills</u>						
IQ Measured at High School	0.006 (0.001)	0.005 (0.001)	0.005 (0.001)	0.006 (0.001)	0.006 (0.001)	0.005 (0.001)
High School Rank	--	--	--	0.001 (0.001)	0.000 (0.001)	0.001 (0.001)
<u>Firm's technology</u>						
Firm Size Dummies	NO	NO	NO	YES	YES	YES
Industry Type Dummies	NO	NO	NO	YES	YES	YES
<u>Additional covariates</u>						
Tenure	0.016 (0.001)	0.016 (0.001)	0.017 (0.001)	0.014 (0.001)	0.014 (0.001)	0.014 (0.001)
Adult Cognition Score	0.001 (0.005)	0.000 (0.006)	−0.001 (0.006)	0.011 (0.005)	0.010 (0.005)	0.009 (0.005)
Pseudo-R ²	0.19	0.20	0.21	0.24	0.24	0.25
Sample Size	1,735	1,733	1,733	1,614	1,612	1,612

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

Table 9A: Mismatch and compensating wage differentials.
Alternative measures II.
OLS estimates for men.
Dependent variable: ln(hourly wage)

	(1)	(2)	(3)	(4)	(5)	(6)
Job Routinization	-0.138 (0.020)	-0.118 (0.021)	-0.077 (0.026)	-0.165 (0.022)	-0.143 (0.022)	-0.099 (0.028)
Routine-Preferring Worker 1	--	0.090 (0.021)	0.114 (0.023)	--	0.094 (0.022)	0.120 (0.024)
Routine-Preferring Worker 2	--	0.042 (0.037)	0.062 (0.037)	--	0.013 (0.038)	0.035 (0.039)
Mismatch	--	--	-0.050 (0.019)	--	--	-0.051 (0.020)
Completed Years of Education	0.049 (0.004)	0.048 (0.004)	0.047 (0.004)	--	--	--
<u>Workers' skills</u>						
IQ Measured at High School	0.003 (0.001)	0.003 (0.001)	0.003 (0.001)	0.004 (0.001)	0.004 (0.001)	0.004 (0.001)
High School Rank	--	--	--	0.001 (0.000)	0.001 (0.000)	0.001 (0.000)
<u>Firm's technology</u>						
Firm Size Dummies	NO	NO	NO	YES	YES	YES
Industry Type Dummies	NO	NO	NO	YES	YES	YES
<u>Additional covariates</u>						
Tenure	0.009 (0.001)	0.009 (0.001)	0.009 (0.001)	0.006 (0.001)	0.006 (0.001)	0.006 (0.001)
Adult Cognition Score	0.006 (0.003)	0.005 (0.003)	0.005 (0.003)	0.011 (0.003)	0.009 (0.003)	0.009 (0.003)
R ²	0.27	0.28	0.28	0.25	0.26	0.27
Sample Size	1,647	1,644	1,644	1,521	1,518	1,518

Notes: Heteroskedasticity robust standard errors are reported in parentheses.

Table 10A: Mismatch and compensating wage differentials.**Alternative measures II.****OLS estimates for women.****Dependent variable: ln(hourly wage)**

	(1)	(2)	(3)	(4)	(5)	(6)
Job Routinization	-0.156 (0.022)	-0.131 (0.023)	-0.096 (0.026)	-0.180 (0.023)	-0.156 (0.023)	-0.117 (0.026)
Routine-Preferring Worker 1	--	0.106 (0.018)	0.134 (0.021)	--	0.109 (0.018)	0.140 (0.021)
Routine-Preferring Worker 2	--	0.022 (0.030)	0.041 (0.031)	--	0.030 (0.033)	0.050 (0.033)
Mismatch	--	--	-0.045 (0.019)	--	--	-0.048 (0.019)
Completed Years of Education	0.045 (0.005)	0.044 (0.005)	0.044 (0.005)	--	--	--
<u>Workers' skills</u>						
IQ Measured at High School	0.005 (0.001)	0.005 (0.001)	0.005 (0.001)	0.006 (0.001)	0.005 (0.001)	0.005 (0.001)
High School Rank	--	--	--	0.001 (0.000)	0.000 (0.000)	0.000 (0.000)
<u>Firm's technology</u>						
Firm Size Dummies	NO	NO	NO	YES	YES	YES
Industry Type Dummies	NO	NO	NO	YES	YES	YES
<u>Additional covariates</u>						
Tenure	0.015 (0.001)	0.015 (0.001)	0.015 (0.001)	0.012 (0.001)	0.012 (0.001)	0.012 (0.001)
Adult Cognition Score	0.003 (0.003)	0.003 (0.003)	0.004 (0.003)	0.008 (0.003)	0.008 (0.003)	0.008 (0.003)
R ²	0.31	0.32	0.32	0.37	0.39	0.39
Sample Size	1,735	1,733	1,733	1,614	1,612	1,612

Notes: Heteroskedasticity robust standard errors are reported in parentheses.