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

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ABSTRACT

This paper attempts to provide a new explanation for why labor economists typically have not been able to find much evidence on compensating wage differentials for job disamenities except for risk of death. The key idea is that although workers need to be compensated when their preferences do not match the work requirements to perform a job task, the occurrence of mismatch decreases productivity as well, reducing the surplus to be divided between workers and firms and decreasing wages. I focus on the match between workers' preferences for routine work and the variability in tasks associated with the job. Using data from the Wisconsin Longitudinal Study, consistent with my model I find that mismatched workers report lower job satisfaction and earn lower wages. I also find that mismatched male workers are more likely to retire earlier from the labor force. Both male and female workers in routinized jobs earn, on average, 12% less than their counterparts in non-routinized jobs. However, once preferences and mismatch are accounted for, this difference decreases to 8% and 5%, for men and women, respectively.

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# 1 Introduction

For more than 30 years, labor economists have endeavored to find evidence of wage premiums on jobs that involve disamenities like physical effort, routine work, or job insecurity. According to the theory of compensating wage differentials, which goes back to Adam Smith and uses the framework of analysis outlined by Rosen (1974), ceteris paribus, workers must receive a wage premium for suffering from job disamenities. However, a survey of the evidence concluded that "*tests of the theory of compensating wage differentials are inconclusive with respect every job characteristic except risk of death*" (Borjas, 2005, Chapter 6, p. 224, italics added).

It is clear that on-the-job risk of death is an undesirable job characteristic, and the available empirical evidence does suggest that wage is 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 tastes or personalities. Smith (1979) notes that the heterogeneity of worker tastes poses a difficulty for testing the theory of compensating wage differentials.

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 mixture is even more striking. Daniel and Sofer (1998) present mixed results in the same paper[1].

A straightforward way to account for preference heterogeneity when looking for compensating wage differentials consists of running separate wage regressions for workers with different preferences. Nevertheless, as I will 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. Thus, preference heterogeneity by itself does not provide an

[1] On the one hand, their OLS estimates show that repetitive work is negatively (positive) associated with wages in strong (weakly) unionized sectors, although these are not statistically significant. On the other hand, they obtain reversed signed estimates, which are statistically significant, when they use 2SLS estimation.

explanation for the puzzle on compensating wage differentials.

Why, even after accounting for preference heterogeneity, compensating wage differentials are not observed? What if workers' preferences for a type of job (or job attribute) are related to the productivity of these workers in performing such a type of job? A worker's taste for a job attribute may correlate with her *comparative advantage* in such a job. This is not the same as saying that preferences may have a direct effect on wages independent on the type of job, i.e., workers with different preferences may have different *absolute advantage* in performing any job. Here, the key insight 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 was perfect and each worker was assigned to a job according to her comparative advantage, the marginal routine-preferring worker should be willing to pay for working in a routinized job. Likewise, 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 pointed out by Lang and Majumdar (2004), 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 those who are attached to an occupation and a geographic location in which jobs with their skills are currently scarce. Here, a similar point can be made replacing the word unemployed by mismatched. As I will show, mismatch between workers' preferences and job attributes exist, and must be taken into account when looking for compensating wage differentials.

I offer a very simple assignment model with Nash bargaining over wages to analyze the role of mismatch on wages. If mismatch is just a disamenity and has no effect on worker productivity, my model is consistent with the standard prediction of the theory of compensating wage differentials: workers are compensated for being mismatched (compensating wage differential effect). However, once mismatch is acknowledged to affect worker's output (productivity effect), the effect of mismatch on the wage rate is ambiguous. Although workers need to be compensated when their preferences do not match the work requirements to perform a job task, the occurrence of mismatch decreases productivity as well, reducing the surplus to be divided between workers and firms and decreasing wages.

This simple framework offers a rationale for the existence of mixed compensating wage differentials estimates. The standard estimates in the compensating wage differentials literature may confound the effect of the job attribute under analysis on wages with the one due to mismatch.

The focus of this paper is on job routinization (i.e., jobs involving repetitive and routine tasks). I consider this is a worthwhile job attribute to study because there are well-documented mixed estimates for this job attribute in the literature (e.g., Lucas, 1977, Brown, 1980, Daniel and Sofer, 1998). Hence, an analysis of compensating wage differentials estimates for such a kind of job attribute may shed new light on the sources of these mixed results. Furthermore, workers in my sample report "being able to do different things rather than the same things over and over" as "much more important than high pay" at the top of the ranking among other job attributes (see Table 1). This suggests that it should be easier to find compensating wage differentials for job routinization than for other job attributes[2].

**[INSERT TABLE 1 ABOUT HERE]**

Using data from the 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, and that

[2] The original table (Table 2, page 52, Andrew et al., 2006) reports also the following job characteristics: having a job that provides health insurance and having a job that provides a pension plan (both of them higher ranked than being able to do different things) and having a low risk of losing your job, being able to decide what time to come to work and when to leave, and having a large number of paid vacation days (all of them lower ranked). However, the preference for each of these attributes is likely to be related to family considerations too (i.e., involving not only individual tastes but also household preferences).

mismatched male workers are more likely to retire earlier from the labor force than well-matched workers.

Looking at compensating wage differentials for job routinization, my results show that, on average, male workers in routinized jobs are paid 12% less than workers in non-routinized jobs, after accounting for differences in IQ, 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 to 8% the difference in average wages between male workers in routinized and those in non-routinized jobs. For female workers, the difference decreases from 12% to 5%.

The fact that the average difference in wages between routinized and non-routinized jobs is reduced from 12% to 8% for men (5% for women) once preferences and mismatch are accounted for suggests that, when mismatch is not accounted for, job routinization is (in part) picking up the negative productivity effect of mismatch on wages, which seems to dominate the positive compensating wage differential effect.

This paper is laid out as follows. Section 2 describes briefly the puzzle in the compensating wage differentials literature. Section 3 presents a model to shed light on the puzzle. In Section 4 I link the puzzle with the predictions of my model. Section 5 describes the WLS dataset, the econometric specifications and show some descriptive statistics. I present my results in Section 6. Section 7 offers some robustness checks. I discuss the caveats of my analysis in Section 8. Finally, Section 9 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 were different. Rosen (1974) formalizes Adam Smith's ideas showing that, under perfect competition, identical workers need to be compensated for job disamenities[3].

The standard method used to test the prediction of this theory consists of estimating a wage regression with characteristics of the job ($z$) and personal characteristics ($p$). In general, the equation estimated is of the form:

$$\ln(w) = \alpha + \beta z + \rho p + \varepsilon \tag{1}$$

For an undesirable job attribute, the theory predicts $\beta > 0$. However, the empirical evidence on compensating wage differentials for job characteristics other than the risk of death is mixed.

Several previous attempts have been made to solve this puzzle. First, estimates may suffer from sorting bias: workers choosing a job with a specific undesirable attribute are the ones with lower distaste for such an attribute (e.g., Kostiuk, 1990). Second, working conditions are endogenously determined: richer individuals are more able to bargaining over working conditions than poorer individuals (e.g., Garen, 1988). Third, omitted variables can also lead to biased estimates due to the correlation between unobserved skills, individual productivities, and quality of working conditions (e.g., Brown, 1980, Duncan and Holmlund, 1983, Hwang, Reed and Hubard, 1992). Fourth, when working conditions are reported by the workers themselves, the estimates are likely to suffer from simultaneity bias (e.g., McNabb, 1989). Not only this but, if answers to survey questions regarding working conditions are given in subjective scales, 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.

Let me focus on the first kind of explanation (sorting bias). Specifically, let me consider the implication of heterogeneity in individual preferences about the attractive or unattractive

[3] A classical disussion on the theory of equalizing differences is offered in Rosen (1986). Chapter 7 in Polacheck and Siebert (1993), chapter 5 in Cahuc and Zylberberg (2004), and chapter 6 in Borjas (2005), provide excellent reviews on the theory of compensating wage differentials.

features of performing a job task for the estimated compensating wage differential estimate. Suppose there are two kind of workers: those who like $z$ ($x = 1$) and those who have a distaste for $z$ ($x = 0$). In that case, to test the theory of compensating wage differentials, the following regressions should be run:

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

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

If the theory is true, I should expect to find evidence on $\beta_0 > 0$ and $\beta_1 < 0$: workers who have a distaste for $z$ ($x = 0$) are compensated for working in a job involving high levels of $z$, while workers who like $z$ ($x = 1$) are willing to pay for working in a job involving high levels of $z$.

**[INSERT TABLE 2 ABOUT HERE]**

However, Table 2 presents evidence contrary to the theory of compensating wage differentials: *workers with lower preference for routine and simple work, earn lower wages in routinized jobs.* In Table 2 job routinization is measured as the fraction of working time doing the same things over and over on the job and routine-preferring workers ($x = 1$) are defined as those individual 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". Column (2) shows that non-routine-preferring male workers do not seem to be compensated for working in routinized jobs; rather, if anything, they appear to be penalized. As the table makes clear, 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 they are paid. For routine-preferring workers, I do not find a statistical significant association between job routinization and hourly wages. Similar conclusions can be drawn from Table 3 for women.

**[INSERT TABLE 3 ABOUT HERE]**

Notice that controlling for education, IQ, and high school rank seems to be a credible way to control for workers' skills. Moreover, controlling for both firm size and industry dummies helps to account for differences in firms' technologies. Furthermore, a careful inspection of tables 2 and 3 reveals that the coefficients on the covariates are very similar for both groups of workers (routine- and non-routine-preferring workers), and indeed statistically indistinguishable. Overall, both the fact that the results do not change after controlling for a rich set of covariates and the stability of the estimated coefficients for both groups of workers suggest that concerns about omitted unobservable variables do not seem to be crucial in this setting. In other words, it seems reasonable to assume that the rest of unobservable abilities (after controlling for observable abilities) are captured by the constant terms in these regressions, which are not reported. Then, the difference in these constant terms captures any (potential) fixed difference in ability between routine- and non-routine-preferring workers. Hence, after looking at tables 2 and 3, the bottom line is that, clearly, preference heterogeneity by itself does not provide an explanation of why compensating wage differentials are not observed.

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 for that. There is no room for productivity considerations: since non-routine-preferring workers have a higher disutility when working in routinized jobs they must be compensated for working in these jobs. What if preference heterogeneity is related to heterogeneity in comparative advantage? 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, the higher is the discrepancy between preferences and job attributes (characteristics or job tasks), and their comparative advantage on the job, which will be lower, the higher is the discrepancy between preferences and job attributes.

If matching was perfect, and each worker was assigned to each job according to her comparative advantage, the productivity effect due to comparative advantage would not play any role: productivity would be the same for every worker, since every worker would be assigned to a job where her comparative advantage is maximum. However, matching is imperfect, and neglecting its influence on wages is likely to confound the compensating wage differentials estimates.

To understand the estimates on tables 2 and 3, 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:

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

and assuming that $E(\varepsilon|z, x) = 0$, figure 1 summarizes the expected log wages for each worker-job pair:

**[INSERT FIGURE 1 ABOUT HERE]**

Tables 2A and 3A in the appendix, report similar estimates to those in tables 2 and 3 but using a binary indicator for job routinization rather than a continuous variable. Notice that the coefficients $\beta_0$ and $\beta_1$ 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 $\delta$ is picking upthe mismatch effect. On the one hand, workers need to be compensated for performing a job (task) that they do not like. On the other hand, workers in jobs that do not match their preferences, will have a negative effect on the match surplus, and firms will push down their wages.

Thus, a potential explanation for the puzzling results in tables 2 and 3 is that preferences for performing a job and worker's comparative advantage in performing such a job are (positively) correlated. If this is the case, *workers with lower preference for routine and simple work, earn lower wages in routinized jobs*, not because they are not compensated for taking such a job, but because they are less productive in performing such a job, and this mismatch productivity effect dominates the compensating wage differential effect. Indeed, my estimates suggest that $\delta < 0$. The idea about the double effect of mismatch on wages is formalized in the next section.

# 3 The Model

In this section I present a very 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 compensating wage differentials estimates.

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 assymetries between firms and workers or geographical dispersion of jobs and workers) and they randomly pick up one of the available jobs[4]. Wage determination occurs through generalized Nash bargaining (interpretations of such a solution in terms of strategic bargaining theory are given in Rogerson, Shimer and Wright, 2005). To simplify the problem,

[4]In Shimer (2007) workers and jobs are randomly allocated to labor markets. My model just assumes 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 of 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 difficult to 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 due to geographical dispersion are also important.

the threat points are assumed to be zero. These two assumptions allow to focus my attention on the main idea of the model: mismatch not only affects worker's disutility, but it also affects worker's productivity.

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 chosen but taken as randomly given. Once the matching is completed, the firm $z$ and the worker $x$ bargain over the division of the match surplus to decide the optimal wage. Let me consider two cases: the benchmark case, with no mismatch productivity effect, and the new case, with mismatch productivity effect.

## 3.1 The Benchmark Case: Mismatch is just a disamenity

The profit function of the firm is given by

$$\pi = A - w \tag{5}$$

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

The utility function of the worker is given by

$$u(m(z,x)) = w - v(m(z,x)) \tag{6}$$

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 $x$. Mismatch can be seen then as a disamenity, $v' > 0$. Tinbergen (1975) supposes 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

$$\max_{w} \left\{ \pi^{\theta} u(m(z,x))^{1-\theta} \right\} \tag{7}$$

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

The FOC gives us the optimal wage rate:

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

The benefits for the firm and the worker are:

$$\pi^{*}(m(z,x)) = \theta \left[ A - v(m(z,x)) \right] \tag{9}$$

$$u^{*}(m(z,x)) = (1-\theta) \left[ A - v(m(z,x)) \right] \tag{10}$$

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

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

Mismatch, which is a disamenity, does affect the wage rate positively, which 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 played a role of a *pure* disamenity. However, mismatch is also likely to affect the firm gross revenue (output). A worker can be compensated for the disutility of performing a routinized job because he does not like repetitive things. However, his distaste (preferences) for doing repetitive things cannot be modified by this compensation. This distaste is likely to be negatively correlated with his ability in doing 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 her comparative advantage on such a type of job are likely to be positively correlated. In this more general case, the profit function of the firm may be rewritten as

$$\pi(m(z,x)) = A(m(z,x)) - w \tag{12}$$

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 which depends on the extent to which a person's abilities match those required in the execution of a job task.

The utility function is still given by (6), and the solution to the Nash bargaining problem must acknowledge that the profit function now is different. Again, the FOC gives us the optimal wage rate:

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

The benefits for the firm and the worker are:

$$\pi^*(m(z,x)) = \theta\left[A(m(z,x)) - v(m(z,x))\right] \tag{14}$$

$$u^*(m(z,x)) = (1-\theta)\left[A(m(z,x)) - v(m(z,x))\right] \tag{15}$$

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

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

The expression for the mismatch effect on the wage rate has now two different components. The first term in (16) is the one I obtained before in (11): it is positive and measures the *compensating wage differential effect* due to mismatch. However, there is a new term that does not appear in (11): this term is negative and measures the *productivity effec*t due to mismatch. Hence, the total effect of mismatch is ambiguous[5].

## 3.3 Main Implications of the Model

The previous model leads to two main propositions:

**Proposition 1** *When mismatch also affects gross revenue (output), mismatch has an ambiguous effect on the wage rate. If the productivity effect dominates the compensating wage differential effect, mismatch affects the wage rate negatively. If the productivity effect is dominated by the compensating wage differential effect, mismatch affects the wage rate positively. If both effects cancel out, mismatch has no effect on the wage rate.*

**Proof.** See equation (16). ■

**Proposition 2** *Mismatch has a negative effect on utility.*

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

Proposition 1 has implications to understand compensating wage differentials estimates. Proposition 2 does not allow me to distinguish between 3.1 and 3.2, since in both cases, mismatch has a negative effect on utility. These propositions are empirically investigated in the results section.

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

# 4 A New Look at the Puzzle

According to the previous model, mismatch entails two offsetting effects on wages. On the one hand, mismatched workers need to be compensated for suffering from a disutility due to the discrepancy between their preferences and job attributes. On the other hand, mismatched workers are less productive because their comparative advantage in performing a job task is lower the higher the discrepancy between their preferences and job attributes.

Notice that in the previous model, each worker-firm pair bargain over the match surplus 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, an immediate question arises: what are the implications of my assignment model for standard compensating wage differentials emerging from a market setting? To answer this question, an assumption supported by the data is required, which is the key to my identification strategy: the compensating wage differential would apply to anyone working in the routinized sector (assuming that that 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 sector do not match their preferences. Thus, my model yields three parameters which are captured in (4) and represented in Figure 1: a routine sector main effect (the compensating differential, $\beta$); a routine-preferring worker main effect (the absolute advantage of this type of worker, $\gamma$); and a negative wage effect for workers who are in a sector other than the one that they prefer (the negative productivity effect due to mismatch, $\delta$).

The key identification assumption of my analysis is that 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. I have a rich set of observables, including IQ scores, so this is a plausible assumption.

The estimates reported in Figure 1 are easy to follow with the model presented in the previous section. Nevertheless, it is helfpful to reinterpret them in a standard difference-in-difference framework. Consider the new model captured by the following specification:

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

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:

**[INSERT FIGURE 2 ABOUT HERE]**

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

# 5 Data and Econometric Specifications

I use data from the Wisconsin Longitudinal Study (WLS) of the University of Wisconsin-Madison[6]. 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), 1992-1993 (graduates), 1993-1994 (siblings) and 2003-2005 (graduates and spouses).

[6] 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.

I focus on the 1992-1993 waves, when individuals were in their early fifties. The reason for this decision is based on both information requirements to perform my empirical analysis and sample (size and selectivity) considerations. First, information on workers' preferences is not available prior to the 1992-93 waves. Second, participation in the labor market is higher for people in their fifties (1992-93 waves) than in their sixties (2003-05 waves): 92.4% of men were employed in 1992 while only 47.8% of them were employed in 2004. Finally, this helps to minimize non-random attrition problems.

The WLS dataset offers an opportunity to explore the role of mismatch when looking for compensating wage differentials. It contains a set of individual characteristics such as IQ score, high school rank, education, preferences, wages, job satisfaction, hours of work, number of hours performing different tasks on the job, etc. Moreover, the sample is very homogeneous (high school graduates from Wisconsin high schools in 1957), which makes concerns about omitted variables less important.

My sample is restricted to workers who were both Wisconsin residents and were employed in 1992, and excludes individuals who were working less than 20 hours per week, self-employed, employees of own company, and family workers. Farmer workers and military are also 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 that my estimates are driven by extreme values in the wage distribution, I decide to trim the tails of the ln(wage) distribution at both the 3% bottom and the 3% top.

## 5.1 Definition of the main variables

The main variables of 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 or higher than .5. I compute this fraction as the ratio between the number of weekly hours doing the same things over and over on the job and the total number of weekly working hours. Notice that the reported number of hours can be compared across individuals, which addresses standard subjectivity bias concerns due to workers' subjective assessments on working conditions. Moreover, the fact that the number of hours worked is reported by the workers themselves deals with the misclassification bias due to imprecise matching of average job (occupation or industry) characteristics to individuals who may possess jobs with different average characteristics[7].

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 with the answer given to the 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 question is one of the items asked to provide scores for the Five-Factor Model of Personality Structure, and it is included in the personality section of the 1992-93 questionnaire, separated from the job history or current/last job characteristics sections. Hence, the potential concerns on framing effects are minimized. For workers who agree strongly, moderately or slightly to 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 the absolute value seems to be the most intuitive way to think about the discrepancy between two variables. Notice that for binary indicators, the absolute

[7] 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). Someone may be tempted to say that using average job routinization may help to overcome the simultaneity bias. Even if this was true, the problem is that then an ecological fallacy could be made, i.e., infering individual relationships from aggregate ones.

value deviation is equivalent to the quadratic deviation.

## 5.2 Econometric Specifications

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

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

As **proposition 1** states, depending on the size of the mismatch productivity effect relative to the mismatch compensating wage differential effect, the effect of mismatch 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:

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

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

The model is a simplification of the reality and abstracts from other wage determinants both at the firm and the worker levels. If these wage determinants are correlated with mismatch, omitting them from (19) is going to bias the mismatch estimate. Indeed, mismatch may be related to both firm's technology and worker's skills. Firms with worse *technologies* are likely to pay lower wages and to have more difficulties in searching for and hiring workers who match their types. At the same time, workers with worse *skills* are also 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 and high-school rank. Firms' technologies ($T$) are measured by firm size dummies and industry dummies. Hence, the augmented specification is:

$$\ln w = \alpha + \delta m(z,x) + \Pi S + \Lambda T + u \tag{20}$$

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

$$u^{*}(m(z,x)) = (1-\theta)\left[A(m(z,x)) - v(m(z,x))\right] \tag{21}$$

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

$$u = \varsigma + \varphi m(z,x) + \varrho \tag{22}$$

a negative estimate of $\varphi$ will be consistent with proposition 2.

As a proxy for utility I use job satisfaction[8]. Clark (2004) uses job satisfaction as a measure of the utility associated with working, emphasizing that is a good measure of how a worker feels about his or her job, predicting workers' future behavior (quits, productivity, absenteeism), often better than objective variables such as wage and hours of work in the case of quits. The job satisfaction measure is constructed from the answers 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 is also performed adding some covariates:

$$u = \varsigma + \varphi m(z,x) + \Theta S + \Upsilon T + \xi \tag{23}$$

[8]The use of job satisfaction in empirical work has been rejected to be a useful or interesting measure for economic analysis by economists (and it is still rejected by many economists today). Perhaps, as recognized by Freeman (1978), 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):

$$\ln(w) = \alpha + \beta z + \gamma x + \delta m(z, x) + \varepsilon \tag{24}$$

which I compare with the standard wage equations that do not control either for workers' preferences or mismatch. Of course, additional covariates are also included into (24).

## 5.3 Descriptive Statistics

Table 4 presents the main descriptive statistics of the WLS sample for currently employed individuals (1992-93). A first look at the table shows that, on average, male workers in non-routinized jobs earn \$18.09 per hour, while 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 female workers in routinized jobs earn \$9.33. Although these are unadjusted averages, workers do not seem to be compensated for job routinization. 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: .24 versus .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).

**[INSERT TABLE 4 ABOUT HERE]**

Can mismatch explain the lower wages in routinized jobs at first glance? 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 the 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 male 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 satisfied 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 are on average less educated than men.

Figure 4 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*100), while this percentage is of 57 for women (758/1331*100). For both men and women, the percentage of mismatched workers is lower in non-routinized jobs. This is consistent with the fact that the majority of men and women are non-routine-preferring workers (76% of men, and 82% of women).

**Figure 4.**

| **Distribution of workers across jobs, 1992-93** (number of observations) | $z = 0$ | $z = 1$ |
|---|---|---|
| *Male* | | |
| $x = 0$ | 48% | 34% |
| | (792) | (567) |
| $x = 1$ | 4% | 14% |
| | (69) | (228) |
| *Female* | | |
| $x = 0$ | 33% | 43% |
| | (573) | (758) |
| $x = 1$ | 4% | 20% |
| | (63) | (349) |

An interesting feature in figure 5 is that there are no differences in average wages between mismatched and well-matched routine workers. Indeed, the differences are only found for non-routine-preferring workers.

**Figure 5.**

| **Average wages by worker-job type, US$ 1992-93** (number of observations) | $z = 0$ | $z = 1$ |
|---|---|---|
| *Male* | | |
| $x = 0$ | 18.4 | 15.7 |
| | (792) | (567) |
| $x = 1$ | 14.3 | 14.0 |
| | (69) | (228) |
| *Female* | | |
| $x = 0$ | 11.8 | 9.7 |
| | (573) | (758) |
| $x = 1$ | 8.4 | 8.5 |
| | (63) | (349) |

# 6 Results

## 6.1 Model Estimates: the effect of mismatch in job routinization on wages and job satisfaction

Tables 5, 6, 7 and 8 present the results on propositions 1 and 2. The model prediction regarding the wage effect of mismatch is ambiguous. Table 5 shows that, for men, mismatch is negatively associated with hourly wages. According to my model, this suggests that the (negative) mismatch productivity effect dominates the (positive) mismatch compensating wage differential effect.

Bearing in mind that the model is a simplification of the real world and abstracts from other wage determinants, 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 $-.110$ (column 1) and $-.053$ (column 6). Column (6) may be problematic due to overcontrolling, since it includes completed education and its determinants, IQ at high school and high school rank, at the same time[9].

My favourite specification is perhaps column (9), which leads to an estimate of $-.073$ for the mismatch effect: on average, mismatched male workers earn 7.3% less than well-matched workers. In that model, I am controlling (indirectly) for education through its determinants, namely IQ an high school rank. Notice that in my sample, all individuals have at least high school education, so I am not controlling for education after high school, which indeed seems to be predicted by IQ and high school rank. All specifications are consistent with the same story, but with different intensity.

**[INSERT TABLE 5 ABOUT HERE]**

The results for women are reported in Table 6. These results are qualitatively the same as those for men, but the size of the mismatch effect is estimated to be 50-60% of the size of the one for men depending on the specification.

**[INSERT TABLE 6 ABOUT HERE]**

Overall, tables 5 and 6 are consistent with the idea that the 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 7 and 8, using job satisfaction as a proxy for utility, show that job satisfaction is negatively related to mismatch. Both mismatched male and female workers report lower satisfaction levels. The relationship is robust to the addition of additional covariates. Thus, tables 7 and 8 are consistent with Proposition 2.

[9]Notice also that since I have neither variation in age nor in education below high school, adding education (indeed, adding education above high school) and industry dummies at the same time is likely to cause endogeneity problems. Furthermore, the returns to education are known to be higher for women than for men, and this specification violates that (see column 6 in Table 6).

**[INSERT TABLE 7 ABOUT HERE]**

**[INSERT TABLE 8 ABOUT HERE]**

### 6.2 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). The model is simple and its empirical predictions cannot be rejected by the data. In this subsection, I turn out to 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.

Tables 9 and 10 present the results on the effect of job routinization on wages for men and women. Looking at table 9, column (1) shows that, on average, male workers in routinized jobs earn 10% less than workers in non-routinized jobs. Once the worker's preference for routine work is accounted for, this penalty is reduced to 9%, column (2). Finally, column (3) shows that routinized jobs pay on average 6% less than non-routinized jobs when mismatch is controlled, and that mismatched workers earn, on average, 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 wrong-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. However, once both workers' preferences and mismatch are accounted for, this difference is reduced to 8%.

**[INSERT TABLE 9 ABOUT HERE]**

Table 10 reports similar results for women: the wage penalty associated with routinized jobs decreases from 12% to 5%, columns (4)-(6).

**[INSERT TABLE 10 ABOUT HERE]**

Overall, my most important findings are two. First, mismatch is negatively related to wages. This result is consistent with both my assignment model and with Borghans et al. (2007): people are most productive in jobs that match their style and 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) main effects, offering support for my model. Second, once mismatch is accounted for, the coefficient on job routinization is attenuated. The evident mismatch effect can account for a substantial portion (but not all) of the wrong-signed compensating differential for job routinization that previous analyses would have indicated.

In the next section, I perform several robustness checks.

# 7 Robustness Checks

## 7.1 Validity Test: Alternative Contemporaneous Matching Measure

I assess the reliability of my (self-constructed) mismatch variable with a proxy for the "quality of matching". This new variable is also a binary indicator: 1 if the individual "would like to do 10 years from now the same kind of work that he/she is doing now (1992)", 0 otherwise. I find that mismatched male individuals in 1992 are less likely to prefer to do 10 years from now the same kind of work that they are doing now. However, I do not find any statistically significant relationship for women.

## 7.2 Refutability Test: Alternative Past Matching Measure

In a parallel exercise to the previous one, but with a different purpose, I check the relationship between mismatch in 1992 and the "quality of matching" in 1975. I do not find any relationship between these two variables, either for men or women. For men, the lack of association between mismatch in 1992 and the quality of matching in 1975, given the negative association between mismatch in 1992 and the quality of matching in 1992, serves to refuse that mismatch in 1992 is capturing something idiosyncratic to the worker and unobservable to the researcher, such as unobservable ability correlated to both wages and mismatch. Although I recognize that this is a crude test, it is reassuring. Indeed, it makes more credible to believe that the estimated effect of mismatch on wages is not driven by an omitted variable bias.

## 7.3 Additional Outcomes: Retirement Behavior

It would be informative to explore job mobility patterns according to mismatch status. However, this is difficult with the present data: my sample size decreases by 50% between 1992 (workers are in their early fities) and 2004 (workers are in their early sixties). Nevertheless, I am able to explore retirement behavior according to mismatch status. Table 11 shows that mismatched male workers are more likely to retire earlier from the labor force than well-matched counterparts. Moreover, none of the covariates added into augmented specifications has any predictive power for the probability of being employed in 2004. For women, I do not find any predictive power of mismatch status in 1992 in terms of future retirement behavior, see table 12. These results seem to be consistent with my findings on the correlation between mismatch and the alternative contemporaneous matching measure (see section 7.1.).

**[INSERT TABLE 11 ABOUT HERE]**

**[INSERT TABLE 12 ABOUT HERE]**

## 7.4 Alternative Measures of Mismatch: Using More Information

The approach used to measure the main variables of the paper in tables 9 and 10 is very neat and clear-cut, however, it does not take full advantage of all the available information contained in my data set. For this reason, I also use a mixed approach: *job routinization* is measured as a continuous variable, *worker's preferences* is measured by several binary indicators, and *mismatch* is measured as before. More specifically, the new *job routinization* variable is measured as the fraction of working time doing the same things over and over on the job. *Worker's preference for routine* is captured by several binary indicators: one such that workers agree strongly or moderately; another one such that workers agree slightly, neither agree nor disagree, or disagree slightly; finally, one such that workers disagree moderately or strongly. Finally, *mismatch* between job routinization and worker's preference for routine and simple work is measured as before. As tables 13 and 14 make clear, the results are very similar than those previously reported in tables 9 and 10.

**[INSERT TABLE 13 ABOUT HERE]**

**[INSERT TABLE 14 ABOUT HERE]**

I also used a discrete approach with alternative cutoffs to define the type of job, the type of worker, and mismatch. In this case, a job was classified as a routinized job if the fraction of time doing the same things over and over was higher than the third quartile on the distribution of the fraction of time, and a worker was classified as a routine-preferring worker if her score on the preference for work that is routine and simple was higher than the third quartile on the distribution of preferences. This alternative approach led to similar results than those reported in tables 9 and 10.

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) are .086 (statistically significant at the 5%) and .080 (statistically significant at the 1%), respectively. For women, these coefficients are .151 and .142, both of them statistically significant at the 1%.

## 7.5 Omitted Controls: Cognition Score

I also checked the sensitivity of my results to the addition of *cognition score*. The motivation for adding the cognition score is to have another control for the worker's individual ability. The total cognition score was 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 due to the fact that the general ability of the sample is high enough to cause little variation in response to simple items. An example of the questions asked to compute the cognition score is: "In what way are an orange and a banana alike?". The addition of the total cognition score did not affect my previous estimates. These results are available from the author upon request.

## 7.6 Extreme Values in the Wage Distribution: Quantile Estimates

Although I trimmed both the bottom 3% and the top 3% of the wage distribution to avoid the influence of extreme values, I decided to perform a median regression analysis through quantile regression to make sure that my OLS estimates of the mismatch effect are not driven by extreme values of the wage distribution. These new estimates were very similar as those obtained in the OLS analysis. Although these estimates are not reported in the paper, they are available from the author upon request.

# 8 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 to think about the implications of mismatch when looking for the existence of compensating wage differentials. Moreover, since mismatch is taken as given, the model does not restrict its possible determinants.

However, taking mismatch as given has its own limitations. In order to evaluate the net gains from reducing or eliminating mismatch, the costs associated with such a policy need to be estimated. Unfortunately, since the determinants of mismatch are not defined, such a cost-benefit analysis cannot be performed[10]. Of course, it must also be recognized that this limitation avoids the possibility of drawing conclusions from dubious specifications.

My data set is good enough to provide the first attempt in understanding the role of mismatch on compensating wage differentials, but it is not the ideal one. First, the sample under analysis is in their early fifties, which poses a limit to the analysis of mismatch on job mobility. Second, mismatch can only be studied for the job routinization attribute. A richer data set would contain longitudinal information on young workers and several job attributes, ideally measured at the firm level, and then perfectly matched with the workers' data on an individual basis. Such a data set would be very useful to look at the evolution of mismatch over time and its implications for job mobility patterns, and to assess the implications of mismatch in multiple dimensions as well.

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

[10] An upper bound to the gross gains from eliminating mismatch can be estimated easily. Using the model specified in column (6) from table 9, 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 these quantities are expressed in US dollars of 1992.

for which I am able to control using 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 worker's skills and firm's technologies. Furthermore, both the validity and refutability tests seem to indicate that mismatch is not capturing some sort of negative ability signal that may affect wages negatively.

# 9 Conclusions

My goal in this paper has been to argue that previous estimates on compensating wage differentials for many job attributes are inconclusive because the discrepancy between workers' preferences and job attributes has not been accounted for. Both casual empiricism and research suggest that this discrepancy does indeed exist. Indeed, in my sample, 38% of men and 47% of 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 his type (preferences). This is the compensating wage differential effect: mismatch does increase wages. However, on the other hand, mismatched workers are less productive in performing a job (task) that does not match his type (preferences), since workers' preferences are likely to correlate with their comparative advantage. This is the productivity effect: mismatch decreases wages. Thus, the effect of mismatch on wages is ambiguous. If mismatch is not accounted for, the association between wages and job attributes may be picking up the correlations between job attributes, preferences and mismatch.

I offer a very simple assignment model with Nash bargaining over wages where 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 mismatch is just a disamenity. However, once mismatch reduces the match surplus as well, there is a negative effect on wages. Thus, in this last case, the effect of mismatch is ambiguous. In both cases, the effect on worker's utility and firm's profits is negative.

My empirical analysis uses the Wisconsin Longitudinal Study (WLS) and it is focused on job routinization (the fraction of working time doing the same things over and over). The main reason for studying such a job attribute is that people in my sample rank "being able to do different things on the job as much more important than high pay" in first position with respect to other job attributes.

I present several pieces of empirical evidence on the validity of my model. First, mismatch is negatively related to wages, which is consistent with the case in which the negative mismatch productivity effect dominates the positive compensating wage differential effect. Second, I find that job satisfaction is negatively related to mismatch. Finally, for male workers, mismatch in 1992 (when they were in their early fifties) is negatively related to the probability of being employed in 2004 (when they were in their early sixties).

I also report the implications of omitting mismatch and workers' preferences from wage regressions when assessing the role of job routinization on wages. 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 account for a substantial portion (but not all) of the wrong-signed compensating wage differential for job routinization that previous analyses would have indicated.

In my view, this paper makes points towards a new way to assess the existence of compensating wage differentials. Clearly, as discussed in the caveats section, much more work on the theoretical front needs to be done, for instance, endogenizing mismatch. Nevertheless, I anticipate that, as long as there are search frictions that ensure that some workers remain in jobs other than those that are 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 sort of frictions seem realistic.

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## FIGURES

| **Figure 1.** **E(ln $w$\| $z$, $x$)** | | | |
|---|---|---|---|
| *Job Type* *Worker Type* | $z$ = 0 (Non-Routinized Job) | $z$ = 1 (Routinized Job) | E(ln $w$ \| $x$, $z$ = 1) – E(ln $w$ \| $x$, $z$ = 0 ) |
| $x$ = 0 (Non-Routine-preferring worker) | $\alpha$ | $\alpha+\beta+\delta$ | $\beta+\delta$ |
| $x$ = 1 (Routine-preferring worker) | $\alpha+\gamma+\delta$ | $\alpha+\beta+\gamma$ | $\beta-\delta$ |

| **Figure 2.** **E(ln $w$\| $z$, $x$)** | | | |
|---|---|---|---|
| *Job Type* *Worker Type* | $z$ = 0 (Non-Routinized Job) | $z$ = 1 (Routinized Job) | E(ln $w$ \| $x$, $z$ = 1) – E(ln $w$ \| $x$, $z$ = 0 ) |
| $x$ = 0 (Non-Routine-preferring worker) | $\alpha^*$ | $\alpha^*+\beta^*$ | $\beta^*$ |
| $x$ = 1 (Routine-preferring worker) | $\alpha^*+\gamma^*$ | $\alpha^*+\beta^*+\gamma^*+\delta^*$ | $\beta^*+\delta^*$ |
| E(ln $w$ \| $z$, $x$ = 1) – E(ln $w$ \| $z$, $x$ = 0 ) | $\gamma^*$ | $\gamma^*+\delta^*$ | $\delta^*$ |

**TABLES**

**Table 1.**
**Percent of currently employed individuals saying *job characteristic* is "much more important than high pay", WLS 1993 wave.**

| *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: Andrew et al. (2006)

**Table 2. Job Routinization and Wages according to Worker's Preferences**
**OLS Estimates for Men. Dependent variable: log (hourly wage)**

| | Worker's Preference | | Worker's Preference | | Worker's Preference | | Worker's Preference | |
|---|---|---|---|---|---|---|---|---|
| | Routine | Non-Routine | Routine | Non-Routine | Routine | Non-Routine | Routine | Non-Routine |
| | (1) | (2) | (3) | (4) | (5) | (6) | (7) | (8) |
| **Job Routinization** | –.024 | –.160*** | –.014 | –.111*** | –.016 | –.101*** | –.034 | –.104*** |
| *(1 if fraction of weekly worked hours doing the same things over and over >= .5 , 0 else)* | (.040) | (.018) | (.039) | (.018) | (.039) | (.018) | (.042) | (.019) |
| Completed years of education | - | - | .050*** | .052*** | .042*** | .045*** | .041*** | .046*** |
| | | | (.013) | (.004) | (.013) | (.004) | (.013) | (.004) |
| Worker's skills | | | | | | | | |
| IQ measured at High School | - | - | - | - | .002* | .003*** | .002 | .003*** |
| | | | | | (.001) | (.001) | (.002) | (.001) |
| High School Rank | - | - | - | - | - | - | .001 | .000 |
| | | | | | | | (.001) | (.000) |
| Firm's technology | | | | | | | | |
| Firm size dummies | NO | NO | NO | NO | NO | NO | NO | NO |
| Industry dummies | NO | NO | NO | NO | NO | NO | NO | NO |
| $R^2$ | .00 | .05 | .05 | .17 | .06 | .18 | .07 | .19 |
| N | 297 | 1,359 | 297 | 1,359 | 297 | 1,359 | 273 | 1,261 |

Note: All regressions include a constant term. Robust standard errors in parentheses.
*** significant at the 1%, ** significant at the 5%, * significant at the 10%

**Table 2. Job Routinization and Wages according to Worker's Preferences**
**OLS Estimates for Men. Dependent variable: log (hourly wage)**

***(continuation)***

| | Worker's Preference | | Worker's Preference | | Worker's Preference | | Worker's Preference | |
|---|---|---|---|---|---|---|---|---|
| | Routine | Non-Routine | Routine | Non-Routine | Routine | Non-Routine | Routine | Non-Routine |
| | (9) | (10) | (11) | (12) | (13) | (14) | (15) | (16) |
| **Job Routinization** | –.042 | –.100*** | –.037 | –.092*** | –.046 | –.124*** | –.037 | –.115*** |
| *(1 if fraction of weekly worked hours doing the same things over and over >= .5 , 0 else)* | (.042) | (.018) | (.041) | (.018) | (.042) | (.019) | (.042) | (.019) |
| Completed years of education | .040*** | .046*** | .055*** | .055*** | - | - | - | - |
| | (.014) | (.004) | (.016) | (.005) | | | | |
| Worker's skills | | | | | | | | |
| IQ measured at High School | .002 | .003*** | .002 | .003*** | .003* | .005*** | .003* | .005*** |
| | (.002) | (.001) | (.002) | (.001) | (.002) | (.001) | (.002) | (.001) |
| High School Rank | .000 | .000 | –.000 | .000 | .001 | .001*** | .001 | .001*** |
| | (.001) | (.001) | (.001) | (.000) | (.001) | (.000) | (.001) | (.000) |
| Firm's technology | | | | | | | | |
| Firm size dummies | YES | YES | YES | YES | YES | YES | YES | YES |
| Industry dummies | NO | NO | YES | YES | NO | NO | YES | YES |
| $R^2$ | .11 | .24 | .21 | .28 | .08 | .17 | .17 | .21 |
| N | 273 | 1,257 | 273 | 1,255 | 273 | 1,257 | 273 | 1,255 |

Note: All regressions include a constant term. Robust standard errors in parentheses.
*** significant at the 1%, ** significant at the 5%, * significant at the 10%

**Table 3. Job Routinization and Wages according to Worker's Preferences**
**OLS Estimates for Women. Dependent variable: log (hourly wage)**

| | Worker's Preference | | Worker's Preference | | Worker's Preference | | Worker's Preference | |
|---|---|---|---|---|---|---|---|---|
| | Routine | Non-Routine | Routine | Non-Routine | Routine | Non-Routine | Routine | Non-Routine |
| | (1) | (2) | (3) | (4) | (5) | (6) | (7) | (8) |
| **Job Routinization** | .008 | −.187*** | .021 | −.135*** | .033 | −.112*** | .042 | −.108*** |
| *(1 if fraction of weekly worked hours doing the same things over and over >= .5 , 0 else)* | (.042) | (.020) | (.043) | (.020) | (.043) | (.020) | (.044) | (.021) |
| Completed years of education | - | - | .073*** | .051*** | .066*** | .041*** | .066*** | .040*** |
| | | | (.017) | (.006) | (.018) | (.006) | (.018) | (.006) |
| <u>Worker's skills</u> | | | | | | | | |
| IQ measured at High School | - | - | - | - | .003** | .005*** | .004** | .005*** |
| | | | | | (.001) | (.001) | (.002) | (.001) |
| High School Rank | - | - | - | - | - | - | −.000 | .001 |
| | | | | | | | (.001) | (.001) |
| <u>Firm's technology</u> | | | | | | | | |
| Firm size dummies | NO | NO | NO | NO | NO | NO | NO | NO |
| Industry dummies | NO | NO | NO | NO | NO | NO | NO | NO |
| $R^2$ | .00 | .06 | .06 | .12 | .07 | .16 | .07 | .16 |
| N | 412 | 1,331 | 412 | 1,331 | 412 | 1,331 | 384 | 1,247 |

Note: All regressions include a constant term. Robust standard errors in parentheses.
*** significant at the 1%, ** significant at the 5%, * significant at the 10%

**Table 3. Job Routinization and Wages according to Worker's Preferences**
**OLS Estimates for Women. Dependent variable: log (hourly wage)**

***(continuation)***

| | Worker's Preference | | Worker's Preference | | Worker's Preference | | Worker's Preference | |
|---|---|---|---|---|---|---|---|---|
| | Routine | Non-Routine | Routine | Non-Routine | Routine | Non-Routine | Routine | Non-Routine |
| | (9) | (10) | (11) | (12) | (13) | (14) | (15) | (16) |
| **Job Routinization** | .003 | −.112*** | −.002 | −.096*** | .004 | −.143*** | .003 | −.118*** |
| *(1 if fraction of weekly worked hours doing the same things over and over >= .5 , 0 else)* | (.041) | (.020) | (.042) | (.020) | (.042) | (.020) | (.042) | (.019) |
| Completed years of education | .073*** | .041*** | .079*** | .035*** | - | - | - | - |
| | (.019) | (.006) | (.019) | (.006) | | | | |
| Worker's skills | | | | | | | | |
| IQ measured at High School | .004** | .004*** | .004** | .005*** | .004*** | .005*** | .004** | .006*** |
| | (.002) | (.001) | (.002) | (.001) | (.002) | (.001) | (.002) | (.001) |
| High School Rank | −.000 | .001** | −.000 | .001* | .001 | .001*** | .001 | .001** |
| | (.001) | (.000) | (.001) | (.000) | (.001) | (.000) | (.001) | (.000) |
| Firm's technology | | | | | | | | |
| Firm size dummies | YES | YES | YES | YES | YES | YES | YES | YES |
| Industry dummies | NO | NO | YES | YES | NO | NO | YES | YES |
| $R^2$ | .22 | .25 | .29 | .31 | .16 | .22 | .23 | .29 |
| N | 381 | 1,241 | 381 | 1,241 | 381 | 1,241 | 381 | 1,241 |

Note: All regressions include a constant term. Robust standard errors in parentheses.
*** significant at the 1%, ** significant at the 5%, * significant at the 10%

**Table 4. Descriptive Statistics.**

| | Men | | | Women | | |
|---|---|---|---|---|---|---|
| | N | Mean | SD | N | Mean | SD |
| **Hourly wage in routinized jobs** | 800 | 15.21 | 4.98 | 1,111 | 9.33 | 3.46 |
| **Hourly wage in non-routinized jobs** | 865 | 18.09 | 6.10 | 637 | 11.41 | 4.19 |
| **(a) Job Routinization: *z*** (1 if fraction of weekly worked hours doing the same things over and over >= .5 , 0 else) | 1,665 | .48 | .50 | 1,748 | .64 | .48 |
| **(b) Routine-Preferring Worker: *x*** (Preference for routine and simple work: 1 if agree strongly/moderately/slightly, 0 disagree strongly/moderately/slightly/ neither agree nor disagree) | 1,656 | .18 | .38 | 1,743 | .24 | .42 |
| **(c) Mismatch: $\|x - z\| = \|(a) - (b)\|$** | 1,656 | .38 | .49 | 1,743 | .47 | .50 |
| **(A) Fraction of weekly worked hours doing the same things over and over** | 1,665 | .48 | .38 | 1,748 | .61 | .37 |

**Table 4. Descriptive Statistics.**
***(continuation)***

| | Men | | | Women | | |
|---|---|---|---|---|---|---|
| | N | Mean | SD | N | Mean | SD |
| **(B) Preference for routine and simple work** | | | | | | |
| *Strongly agree* | 94 | .06 | - | 108 | .06 | - |
| *Moderately agree* | 162 | .10 | - | 238 | .14 | - |
| *Slightly agree* | 35 | .02 | - | 48 | .03 | - |
| *Neither agree nor disagree* | 6 | .00 | - | 18 | .01 | - |
| *Slightly disagree* | 59 | .04 | - | 68 | .04 | - |
| *Moderately disagree* | 447 | .27 | - | 503 | .29 | - |
| *Strongly disagree* | 853 | .52 | - | 760 | .44 | - |
| **Hourly wage for mismatched workers** | 636 | 15.51 | 5.08 | 821 | 9.61 | 3.52 |
| **Hourly wage for 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 | .49 | - | 919 | .52 | - |
| *Fairly satisfied* | 703 | .42 | - | 661 | .38 | - |
| *Somewhat dissatisfied* | 117 | .07 | - | 139 | .08 | - |
| *Very dissatisfied* | 31 | .02 | - | 28 | .02 | - |

**Table 4. Descriptive Statistics.**
***(continuation)***

| | Men | | | Women | | |
|---|---|---|---|---|---|---|
| | N | Mean | SD | N | Mean | SD |
| **IQ** (measured at high school) [61-145] | 1,665 | 98.95 | 14.35 | 1,748 | 100.10 | 13.89 |
| **High school rank** [0-99] | 1,543 | 41.59 | 27.03 | 1,636 | 57.04 | 27.21 |
| **Years of completed education** [12-20] | 1,665 | 13.44 | 2.19 | 1,748 | 12.93 | 1.71 |
| **Cognitions score (WAIS)** [0-15] | 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:
Hourly wages are expressed in $US 1992.

**Table 5. Mismatch and Wages**
**OLS Estimates for Men. Dependent variable: log (hourly wage)**

| | (1) | (2) | (3) | (4) | (5) | (6) | (7) | (8) | (9) |
|---|---|---|---|---|---|---|---|---|---|
| **Mismatch** | −.110*** | −.073*** | −.067*** | −.066*** | −.062*** | −.053*** | −.084*** | −.080*** | −.073*** |
| | (.017) | (.016) | (.016) | (.017) | (.016) | (.016) | (.017) | (.017) | (.017) |
| Completed years of education | - | .059*** | .049*** | .049*** | .049*** | .058*** | - | - | - |
| | | (.003) | (.004) | (.004) | (.004) | (.005) | | | |
| Worker's skills | | | | | | | | | |
| IQ measured at High School | - | - | .004*** | .003*** | .004*** | .004*** | .005*** | .005** | .005*** |
| | | | (.001) | (.001) | (.001) | (.001) | (.001) | (.001) | (.001) |
| High School Rank | - | - | - | .001 | .000 | .000 | .002*** | .002*** | .002*** |
| | | | | (.001) | (.001) | (.001) | (.000) | (.000) | (.000) |
| Firm's technology | | | | | | | | | |
| Firm size dummies | NO | NO | NO | NO | YES | YES | NO | YES | YES |
| Industry dummies | NO | NO | NO | NO | NO | YES | NO | NO | YES |
| $R^2$ | .02 | .16 | .18 | .19 | .24 | .27 | .12 | .16 | .19 |
| N | 1,656 | 1,656 | 1,656 | 1,534 | 1,530 | 1,528 | 1,534 | 1,530 | 1,528 |

Note: All regressions include a constant term. Robust standard errors in parentheses.
*** significant at the 1%, ** significant at the 5%, * significant at the 10%

**Table 6. Mismatch and Wages**
**OLS Estimates for Women. Dependent variable: log (hourly wage)**

| | (1) | (2) | (3) | (4) | (5) | (6) | (7) | (8) | (9) |
|---|---|---|---|---|---|---|---|---|---|
| **Mismatch** | −.079*** | −.042** | −.043*** | −.045*** | −.040** | −.032*** | −.071*** | −.065*** | −.052*** |
| | (.018) | (.017) | (.017) | (.017) | (.017) | (.016) | (.017) | (.017) | (.016) |
| Completed years of education | - | .067*** | .051*** | .049*** | .051*** | .046*** | - | - | - |
| | | (.005) | (.006) | (.006) | (.006) | (.006) | | | |
| Worker's skills | | | | | | | | | |
| IQ measured at High School | - | - | .006*** | .006*** | .005*** | .005*** | .007*** | .007** | .007*** |
| | | | (.001) | (.001) | (.001) | (.001) | (.001) | (.001) | (.001) |
| High School Rank | - | - | - | .001* | .001** | .001** | .001*** | .002*** | .001*** |
| | | | | (.000) | (.000) | (.000) | (.000) | (.000) | (.000) |
| Firm's technology | | | | | | | | | |
| Firm size dummies | NO | NO | NO | NO | YES | YES | NO | YES | YES |
| Industry dummies | NO | NO | NO | NO | NO | YES | NO | NO | YES |
| $R^2$ | .01 | .11 | .15 | .16 | .25 | .30 | .12 | .20 | .27 |
| N | 1,743 | 1,743 | 1,743 | 1,631 | 1,622 | 1,622 | 1,631 | 1,622 | 1,622 |

Note: All regressions include a constant term. Robust standard errors in parentheses.
*** significant at the 1%, ** significant at the 5%, * significant at the 10%

**Table 7. 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** | –.187*** | –.188*** | –.200*** | –.220*** | –.217*** | –.214*** | –.225*** | –.223*** | –.217*** |
| | (.058) | (.058) | (.059) | (.061) | (.064) | (.062) | (.061) | (.061) | (.062) |
| Completed years of education | - | –.003 | .009 | .016 | .016 | .006 | - | - | - |
| | | (.013) | (.014) | (.016) | (.016) | (.018) | | | |
| Worker's skills | | | | | | | | | |
| IQ measured at High School | - | - | –.005** | –.004* | –.005* | –.005** | –.004 | –.004 | –.005* |
| | | | (.002) | (.003) | (.003) | (.003) | (.003) | (.003) | (.003) |
| High School Rank | - | - | - | –.001 | –.001 | –.001 | –.000 | –.000 | –.000 |
| | | | | (.001) | (.001) | (.001) | (.001) | (.001) | (.001) |
| Firm's technology | | | | | | | | | |
| Firm size dummies | NO | NO | NO | NO | YES | YES | NO | YES | YES |
| Industry dummies | NO | NO | NO | NO | NO | YES | NO | NO | YES |
| Pseudo-$R^2$ | .00 | .00 | .00 | .01 | .01 | .01 | .01 | .01 | .01 |
| N | 1,654 | 1,654 | 1,654 | 1,532 | 1,528 | 1,526 | 1,532 | 1,528 | 1,526 |

Note: All regressions include a constant term. Robust standard errors in parentheses.
*** significant at the 1%, ** significant at the 5%, * significant at the 10%

**Table 8. 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** | –.245*** | –.257*** | –.257*** | –.276*** | –.277*** | –.273*** | –.267*** | –.268*** | –.259*** |
| | (.056) | (.057) | (.057) | (.059) | (.059) | (.059) | (.058) | (.058) | (.058) |
| Completed years of education | - | –.023 | –.023 | –.019 | –.021 | –.033* | - | - | - |
| | | (.016) | (.017) | (.018) | (.018) | (.019) | | | |
| Worker's skills | | | | | | | | | |
| IQ measured at High School | - | - | .000 | .001 | .001 | .001 | .001 | .001 | .001 |
| | | | (.002) | (.003) | (.002) | (.003) | (.003) | (.003) | (.003) |
| High School Rank | - | - | - | –.001 | –.001 | –.001 | –.001 | –.001 | –.001 |
| | | | | (.001) | (.001) | (.001) | (.001) | (.001) | (.001) |
| Firm's technology | | | | | | | | | |
| Firm size dummies | NO | NO | NO | NO | YES | YES | NO | YES | YES |
| Industry dummies | NO | NO | NO | NO | NO | YES | NO | NO | YES |
| Pseudo-$R^2$ | .01 | .01 | .01 | .01 | .01 | .02 | .01 | .01 | .01 |
| N | 1,742 | 1,742 | 1,742 | 1,630 | 1,621 | 1,621 | 1,630 | 1,621 | 1,621 |

Note: All regressions include a constant term. Robust standard errors in parentheses.
*** significant at the 1%, ** significant at the 5%, * significant at the 10%

**Table 9. Mismatch and Compensating Wage Differentials**
**OLS Estimates for Men. Dependent variable: log (hourly wage)**

| | (1) | (2) | (3) | (4) | (5) | (6) |
|---|---|---|---|---|---|---|
| **Job Routinization** | –.100*** | –.090*** | –.059*** | –.122*** | –.107*** | –.078*** |
| *(1 if fraction of weekly worked hours doing the same things over and over >= .5 , 0 else)* | (.016) | (.016) | (.021) | (.017) | (.017) | (.022) |
| **Routine-Preferring Worker** | - | –.075*** | –.095*** | - | –.096*** | –.115*** |
| *(Preference for routine and simple work: 1 if agree strongly/moderately/slightly, 0 disagree strongly/moderately/slightly/ neither agree nor disagree)* | | (.020) | (.022) | | (.021) | (.023) |
| **Mismatch** | - | - | –.043** | - | - | –.040* |
| | | | (.021) | | | (.022) |
| Completed years of education | .047*** | .045*** | .045*** | - | - | - |
| | (.004) | (.004) | (.004) | | | |
| <u>Worker's skills</u> | | | | | | |
| IQ measured at High School | .003*** | .003*** | .003*** | .005*** | .004*** | .004*** |
| | (.001) | (.001) | (.001) | (.001) | (.001) | (.001) |
| High School Rank | - | - | - | .001*** | .001*** | .001*** |
| | | | | (.000) | (.000) | (.000) |
| <u>Firm's technology</u> | | | | | | |
| Firm size dummies | NO | NO | NO | YES | YES | YES |
| Industry dummies | NO | NO | NO | YES | YES | YES |
| $R^2$ | .19 | .20 | .20 | .21 | .22 | .22 |
| N | 1,663 | 1,656 | 1,656 | 1,537 | 1,528 | 1,528 |

Note: All regressions include a constant term. Robust standard errors in parentheses.
*** significant at the 1%, ** significant at the 5%, * significant at the 10%

**Table 10. Mismatch and Compensating Wage Differentials**
**OLS Estimates for Women. Dependent variable: log (hourly wage)**

| | (1) | (2) | (3) | (4) | (5) | (6) |
|---|---|---|---|---|---|---|
| **Job Routinization** | −.105*** | −.090*** | −.037 | −.120*** | −.105*** | −.054** |
| *(1 if fraction of weekly worked hours doing the same things over and over >= .5 , 0 else)* | (.018) | (.018) | (.023) | (.018) | (.018) | (.023) |
| **Routine-Preferring Worker** | - | −.109*** | −.155*** | - | −.109*** | −.153*** |
| *(Preference for routine and simple work: 1 if agree strongly/moderately/slightly, 0 disagree strongly/moderately/slightly/ neither agree nor disagree)* | | (.019) | (.023) | | (.019) | (.023) |
| **Mismatch** | - | - | −.075*** | - | - | −.072*** |
| | | | (.023) | | | (.022) |
| Completed years of education | .046*** | .045*** | .044*** | - | - | - |
| | (.006) | (.006) | (.006) | | | |
| Worker's skills | | | | | | |
| IQ measured at High School | .006*** | .005*** | .005*** | .006*** | .005*** | .005*** |
| | (.001) | (.001) | (.001) | (.001) | (.001) | (.001) |
| High School Rank | - | - | - | .001*** | .001** | .001** |
| | | | | (.000) | (.000) | (.000) |
| Firm's technology | | | | | | |
| Firm size dummies | NO | NO | NO | YES | YES | YES |
| Industry dummies | NO | NO | NO | YES | YES | YES |
| $R^2$ | .17 | .18 | .19 | .29 | .30 | .30 |
| N | 1,748 | 1,743 | 1,743 | 1,627 | 1,622 | 1,622 |

Note: All regressions include a constant term. Robust standard errors in parentheses.
*** significant at the 1%, ** significant at the 5%, * significant at the 10%

**Table 11. Mismatch and Early Retirement**
**Probit Estimates for Men (Marginal Effects). Dependent variable: 1 if employed in 2004, 0 otherwise**

| | (1) | (2) | (3) | (4) | (5) | (6) | (7) | (8) | (9) |
|---|---|---|---|---|---|---|---|---|---|
| **Mismatch** | –.065** | –.059*** | –.056** | –.062** | –.069** | –.082*** | –.064** | –.070** | –.083*** |
| | (.027) | (.027) | (.028) | (.029) | (.029) | (.029) | (.029) | (.029) | (.029) |
| Completed years of education | - | .010 | .005 | .006 | .005 | .004 | - | - | - |
| | | (.006) | (.007) | (.007) | (.007) | (.008) | | | |
| Worker's skills | | | | | | | | | |
| IQ measured at High School | - | - | .002* | .001 | .001 | .001 | .002 | .001 | .001 |
| | | | (.002) | (.001) | (.001) | (.001) | (.001) | (.001) | (.001) |
| High School Rank | - | - | - | .000 | .000 | .000 | .000 | .000 | .000 |
| | | | | (.000) | (.000) | (.001) | (.001) | (.001) | (.001) |
| Firm's technology | | | | | | | | | |
| Firm size dummies | NO | NO | NO | NO | YES | YES | NO | YES | YES |
| Industry dummies | NO | NO | NO | NO | NO | YES | NO | NO | YES |
| Proportion of Employed in 2004 | .42 | .42 | .42 | .41 | .41 | .41 | .41 | .41 | .41 |
| Pseudo-$R^2$ | .00 | .00 | .01 | .01 | .02 | .04 | .01 | .02 | .03 |
| N | 1,387 | 1,387 | 1,387 | 1,282 | 1,280 | 1,278 | 1,282 | 1,280 | 1,278 |

Note: Robust standard errors in parentheses.
*** significant at the 1%, ** significant at the 5%, * significant at the 10%

**Table 12. Mismatch and Early Retirement**
**Probit Estimates for Women (Marginal Effects). Dependent variable: 1 if employed in 2004, 0 otherwise**

| | (1) | (2) | (3) | (4) | (5) | (6) | (7) | (8) | (9) |
|---|---|---|---|---|---|---|---|---|---|
| **Mismatch** | .034 | .040 | .040 | .032 | .027 | .024 | .030 | .024 | .022 |
| | (.026) | (.026) | (.026) | (.027) | (.027) | (.027) | (.027) | (.027) | (.027) |
| Completed years of education | - | .010 | .008 | .004 | .006 | .004 | - | - | - |
| | | (.007) | (.008) | (.008) | (.008) | (.009) | | | |
| <u>Worker's skills</u> | | | | | | | | | |
| IQ measured at High School | - | - | .001 | .001 | .001 | .001 | .001 | .001 | .001 |
| | | | (.002) | (.001) | (.001) | (.001) | (.001) | (.001) | (.001) |
| High School Rank | - | - | - | .000 | .000 | .000 | .000 | .000 | .000 |
| | | | | (.001) | (.001) | (.001) | (.001) | (.001) | (.001) |
| <u>Firm's technology</u> | | | | | | | | | |
| Firm size dummies | NO | NO | NO | NO | YES | YES | NO | YES | YES |
| Industry dummies | NO | NO | NO | NO | NO | YES | NO | NO | YES |
| Proportion of Employed in 2004 | .44 | .44 | .44 | .43 | .44 | .44 | .44 | .44 | .44 |
| Pseudo-$R^2$ | .00 | .00 | .00 | .00 | .01 | .02 | .00 | .01 | .02 |
| N | 1,497 | 1,497 | 1,497 | 1,404 | 1,396 | 1,396 | 1,404 | 1,396 | 1,396 |

Note: Robust standard errors in parentheses.
*** significant at the 1%, ** significant at the 5%, * significant at the 10%

**Table 13. Mismatch and Compensating Wage Differentials**
**OLS Estimates for Men. Dependent variable: log (hourly wage)**

| | (1) | (2) | (3) | (4) | (5) | (6) |
|---|---|---|---|---|---|---|
| **Job Routinization** | –.134*** | –.118*** | –.077*** | –.166*** | –.144*** | –.104*** |
| *(fraction of weekly worked hours doing the same things over and over)* | (.021) | (.022) | (.027) | (.022) | (.023) | (.028) |
| **Routine-Preferring Worker 1** | - | .079*** | .103*** | | .094*** | .118*** |
| *(1 if disagree strongly/moderately, 0 otherwise)* | | (.022) | (.024) | | (.023) | .(025) |
| **Routine-Preferring Worker 2** | - | .035 | .055 | - | .015 | .035 |
| *(1 if disagree slightly/neither agree or disagree/agree slightly, 0 otherwise)* | | (.037) | (.038) | | (.039) | (.040) |
| **Mismatch** | - | - | –.049** | - | - | –.046** |
| | | | (.020) | | | (.021) |
| Completed years of education | .047*** | .045*** | .045*** | - | - | - |
| | (.004) | (.004) | (.004) | | | |
| Worker's skills | | | | | | |
| IQ measured at High School | .003*** | .003*** | .003*** | .005*** | .004*** | .004*** |
| | (.001) | (.001) | (.001) | (.001) | (.001) | (.001) |
| High School Rank | - | - | - | .001*** | .001*** | .001*** |
| | | | | (.000) | (.000) | (.000) |
| Firm's technology | | | | | | |
| Firm size dummies | NO | NO | NO | YES | YES | YES |
| Industry dummies | NO | NO | NO | YES | YES | YES |
| $R^2$ | .19 | .20 | .20 | .21 | .22 | .23 |
| N | 1,665 | 1,656 | 1,656 | 1,537 | 1,528 | 1,528 |

Note: All regressions include a constant term. Robust standard errors in parentheses.
*** significant at the 1%, ** significant at the 5%, * significant at the 10%

**Table 14. Mismatch and Compensating Wage Differentials**
**OLS Estimates for Women. Dependent variable: log (hourly wage)**

| | (1) | (2) | (3) | (4) | (5) | (6) |
|---|---|---|---|---|---|---|
| **Job Routinization** | −.158*** | −.135*** | −.091*** | −.181*** | −.159*** | −.116*** |
| *(fraction of weekly worked hours doing the same things over and over)* | (.024) | (.024) | (.029) | (.023) | (.023) | (.027) |
| **Routine-Preferring Worker 1** | - | .110*** | .146*** | | .108*** | .118*** |
| *(1 if disagree strongly/moderately, 0 otherwise)* | | (.021) | (.024) | | (.020) | .(022) |
| **Routine-Preferring Worker 2** | - | .052 | .075** | - | .050 | .072** |
| *(1 if disagree slightly/neither agree or disagree/agree slightly, 0 otherwise)* | | (.034) | (.035) | | (.035) | (.035) |
| **Mismatch** | - | - | −.057*** | - | - | −.054*** |
| | | | (.021) | | | (.020) |
| Completed years of education | .045*** | .044*** | .043*** | - | - | - |
| | (.006) | (.006) | (.006) | | | |
| <u>Worker's skills</u> | | | | | | |
| IQ measured at High School | .005*** | .005*** | .005*** | .006*** | .005*** | .005*** |
| | (.001) | (.001) | (.001) | (.001) | (.001) | (.001) |
| High School Rank | - | - | - | .001** | .001*** | .001*** |
| | | | | (.000) | (.000) | (.000) |
| <u>Firm's technology</u> | | | | | | |
| Firm size dummies | NO | NO | NO | YES | YES | YES |
| Industry dummies | NO | NO | NO | YES | YES | YES |
| $R^2$ | .17 | .19 | .19 | .29 | .30 | .31 |
| N | 1,748 | 1,743 | 1,743 | 1,627 | 1,622 | 1,622 |

Note: All regressions include a constant term. Robust standard errors in parentheses.
*** significant at the 1%, ** significant at the 5%, * significant at the 10%

## APPENDIX

**Table 2A. Job Routinization and Wages according to Worker's Preferences**
**OLS Estimates for Men. Dependent variable: log (hourly wage)**

| | Worker's Preference | | Worker's Preference | | Worker's Preference | | Worker's Preference | |
|---|---|---|---|---|---|---|---|---|
| | Routine | Non-Routine | Routine | Non-Routine | Routine | Non-Routine | Routine | Non-Routine |
| | (1) | (2) | (3) | (4) | (5) | (6) | (7) | (8) |
| **Job Routinization** | –.000 | –.232*** | –.023 | –.161*** | .023 | –.147*** | .002 | –.151*** |
| *(fraction of weekly worked hours doing the same things over and over)* | (.051) | (.025) | (.052) | (.023) | (.052) | (.024) | (.055) | (.025) |
| Completed years of education | - | - | .051*** | .051*** | .043*** | .045*** | .041*** | .045*** |
| | | | (.013) | (.004) | (.013) | (.004) | (.013) | (.004) |
| <u>Worker's skills</u> | | | | | | | | |
| IQ measured at High School | - | - | - | - | .002* | .003*** | .002 | .003*** |
| | | | | | (.001) | (.001) | (.002) | (.001) |
| High School Rank | - | - | - | - | - | - | .001 | .000 |
| | | | | | | | (.001) | (.000) |
| <u>Firm's technology</u> | | | | | | | | |
| Firm size dummies | NO | NO | NO | NO | NO | NO | NO | NO |
| Industry dummies | NO | NO | NO | NO | NO | NO | NO | NO |
| $R^2$ | .00 | .06 | .05 | .17 | .06 | .18 | .06 | .19 |
| N | 297 | 1,359 | 297 | 1,359 | 297 | 1,359 | 273 | 1,261 |

Note: All regressions include a constant term. Robust standard errors in parentheses.
*** significant at the 1%, ** significant at the 5%, * significant at the 10%

**Table 2A. Job Routinization and Wages according to Worker's Preferences**
**OLS Estimates for Men. Dependent variable: log (hourly wage)**

***(continuation)***

| | Worker's Preference | | Worker's Preference | | Worker's Preference | | Worker's Preference | |
|---|---|---|---|---|---|---|---|---|
| | Routine | Non-Routine | Routine | Non-Routine | Routine | Non-Routine | Routine | Non-Routine |
| | (9) | (10) | (11) | (12) | (13) | (14) | (15) | (16) |
| **Job Routinization** | –.012 | –.143*** | –.016 | –.131*** | –.024 | –.179*** | –.022 | –.163*** |
| *(fraction of weekly worked hours doing the same things over and over)* | (.055) | (.024) | (.056) | (.024) | (.055) | (.025) | (.056) | (.025) |
| Completed years of education | .040*** | .045*** | .055*** | .055*** | - | - | - | - |
| | (.014) | (.004) | (.016) | (.005) | | | | |
| <u>Worker's skills</u> | | | | | | | | |
| IQ measured at High School | .002 | .003*** | .002 | .003*** | .003* | .004*** | .003* | .004*** |
| | (.002) | (.001) | (.002) | (.001) | (.002) | (.001) | (.002) | (.001) |
| High School Rank | .000 | .000 | –.000 | .000 | .001 | .001*** | .001 | .001*** |
| | (.001) | (.000) | (.001) | (.000) | (.001) | (.000) | (.001) | (.000) |
| <u>Firm's technology</u> | | | | | | | | |
| Firm size dummies | YES | YES | YES | YES | YES | YES | YES | YES |
| Industry dummies | NO | NO | YES | YES | NO | NO | YES | YES |
| $R^2$ | .10 | .25 | .21 | .28 | .08 | .18 | .17 | .21 |
| N | 273 | 1,257 | 273 | 1,255 | 273 | 1,257 | 273 | 1,255 |

Note: All regressions include a constant term. Robust standard errors in parentheses.
*** significant at the 1%, ** significant at the 5%, * significant at the 10%

**Table 3A. Job Routinization and Wages according to Worker's Preferences Women**
**OLS Estimates for Women. Dependent variable: log (hourly wage)**

| | Worker's Preference | | Worker's Preference | | Worker's Preference | | Worker's Preference | |
|---|---|---|---|---|---|---|---|---|
| | Routine | Non-Routine | Routine | Non-Routine | Routine | Non-Routine | Routine | Non-Routine |
| | (1) | (2) | (3) | (4) | (5) | (6) | (7) | (8) |
| **Job Routinization** | –.076 | –.264*** | –.038 | –.190*** | –.021 | –.159*** | –.012 | –.149*** |
| *(fraction of weekly worked hours doing the same things over and over)* | (.053) | (.026) | (.055) | (.027) | (.055) | (.027) | (.057) | (.028) |
| Completed years of education | - | - | .071*** | .050*** | .065*** | .039*** | .066*** | .039*** |
| | | | (.018) | (.006) | (.018) | (.006) | (.019) | (.006) |
| Worker's skills | | | | | | | | |
| IQ measured at High School | - | - | - | - | .003** | .005*** | .004** | .005*** |
| | | | | | (.001) | (.001) | (.002) | (.001) |
| High School Rank | - | - | - | - | - | - | –.001 | .001 |
| | | | | | | | (.001) | (.001) |
| Firm's technology | | | | | | | | |
| Firm size dummies | NO | NO | NO | NO | NO | NO | NO | NO |
| Industry dummies | NO | NO | NO | NO | NO | NO | NO | NO |
| $R^2$ | .01 | .07 | .06 | .13 | .07 | .16 | .07 | .16 |
| N | 412 | 1,331 | 412 | 1,331 | 412 | 1,331 | 384 | 1,247 |

Note: All regressions include a constant term. Robust standard errors in parentheses.
*** significant at the 1%, ** significant at the 5%, * significant at the 10%

**Table 3A. Job Routinization and Wages according to Worker's Preferences**
**OLS Estimates for Women. Dependent variable: log (hourly wage)**

***(continuation)***

| | Worker's Preference | | Worker's Preference | | Worker's Preference | | Worker's Preference | |
|---|---|---|---|---|---|---|---|---|
| | Routine | Non-Routine | Routine | Non-Routine | Routine | Non-Routine | Routine | Non-Routine |
| | (9) | (10) | (11) | (12) | (13) | (14) | (15) | (16) |
| **Job Routinization** | –.063 | –.158*** | –.048 | –.136*** | –.087* | –.202*** | –.071 | –.168*** |
| *(fraction of weekly worked hours doing the same things over and over)* | (.053) | (.027) | (.053) | (.026) | (.053) | (.027) | (.052) | (.026) |
| Completed years of education | .071*** | .040*** | .078*** | .034*** | - | - | - | - |
| | (.019) | (.006) | (.019) | (.006) | | | | |
| Worker's skills | | | | | | | | |
| IQ measured at High School | .004** | .004*** | .004** | .005*** | .004** | .005*** | .004** | .006*** |
| | (.002) | (.001) | (.002) | (.001) | (.002) | (.001) | (.002) | (.001) |
| High School Rank | –.000 | .001* | –.000 | .001 | .001 | .001*** | .001 | .001** |
| | (.001) | (.001) | (.001) | (.001) | (.001) | (.000) | (.001) | (.000) |
| Firm's technology | | | | | | | | |
| Firm size dummies | YES | YES | YES | YES | YES | YES | YES | YES |
| Industry dummies | NO | NO | YES | YES | NO | NO | YES | YES |
| $R^2$ | .22 | .25 | .29 | .31 | .17 | .22 | .24 | .29 |
| N | 381 | 1,241 | 381 | 1,241 | 381 | 1,241 | 381 | 1,241 |

Note: All regressions include a constant term. Robust standard errors in parentheses.
*** significant at the 1%, ** significant at the 5%, * significant at the 10%