Changes in Returns to Task-Specific Skills and Gender Wage Gap

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Abstract

How did skilled-biased technological change affect wage inequality, particularly between men and women? To answer that question this paper constructs a task-based Roy model in which workers possess a bundle of basic skills, and occupations are characterized as a bundle of basic tasks. The model is structurally estimated using the task data from the Dictionary of Occupational Titles and the PSID. The main empirical finding is that men have more motor skills than women, but the returns to motor skills have dropped significantly, accounting for more than 40% of the narrowing gender wage gap.

Keywords: Roy model, task-based approach, occupational choice, skill-biased technological change, soft skills.

JEL Codes: J24, J31

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1 Introduction

This paper studies the contribution of the technological change induced by a broad adoption of computers in 1980's and 90's to the narrowing gender wage gap using the task data from the Dictionary of Occupational Titles (DOT) and the Panel Study of Income Dynamics (PSID). Male wage inequality rapidly rose in the 1980's and continued to through the 1990's. Labor economists consider that the technological change since the early 1980's has raised the return to skills, which contributed to increased wage inequality. On the other hand, gender wage gap was stable until 1980 and dramatically decreased afterwards. Despite the fact that the rise of male wage inequality and the fall of gender wage inequality occurred at the same time, many papers, including Blau and Kahn (1997) and Card and DiNardo (2002), do not consider the role that technological change played in narrowing the gender wage gap. They argue that, since men were more educated and experienced than women during this period, the rise in returns to skills caused by the technological change should have widened the gender wage gap. They consider that, despite the technological change being unfavorable to women, the gender wage gap narrowed due to an increase in the measured and unmeasured human capital possessed by women, and possibly a reduction in gender discrimination.

However, when one takes a closer look at the workplace, the technological change seems to have reduced women's disadvantages. Autor, Levy, and Murnane (2003) find that computers replaced routine manual tasks and lowered returns to manual skills relative to nonroutine cognitive skills. Given that manual task intensive jobs (i.e. blue-collar jobs) are typically male-dominated, the technological change was unfavorable to men, not women. Borghans, ter Weel, and Weinberg (2006) show that technological and organizational changes have increased the importance of people skills in the workplace, and that these changes help explain the increase in women's wages relative to men's. Weinberg (2000) provides empirical evidence that the de-emphasis in physical skills following computerization has increased the demand for female workers. Black and Spitz-Oener (2010) and Bacolod and Blum (2010) also find evidence that the shift in demand from manual tasks to analytical tasks plays an important role in the change of the gender wage gap. While these previous contributions provide suggestive evidence for the role of tasks in influencing the gender wage gap, the literature lacks an explicit economic model to interpret the empirical findings. How and why are workers sorted across tasks? How are wages determined according to the workers' skills and tasks? How should skills be measured? These basic questions remain unanswered.

The objective of this paper is twofold. First, I construct and estimate a structural model of occupational choice in which workers possess a bundle of basic skills and occupations are characterized as a bundle of basic tasks. The proposed model demonstrates that heterogeneity in returns to skills across occupations is the key mechanism by which workers with different skill endowments self-select into different occupations. Second, using the estimated model, I quantitatively evaluate the effects of the technological change on the gender wage gap by comparing the actual gender wage gap and the counterfactual gender wage gap under the scenario that the technological change did not occur.

I begin by showing a set of facts about the U.S. labor market from 1979 to 1996 to motivate the structural model. Using the data from the DOT and Current Population Survey (CPS), I show that during that period, motor-task intensive jobs such as craft occupations experienced a large wage loss of around 18%, while cognitive-task intensive jobs such as professionals enjoyed a positive wage growth of 6%. These wage growth patterns are consistent with the predictions of the nuanced-view of technological change proposed by Autor, Levy, and Murnane (2003). Another relevant fact is that the motor-task intensive jobs are male-dominated. For example, craft occupations are the most motor-task intensive jobs and 95% of craft workers are men. This gender difference in occupational distribution implies that the technological change adversely affected men relative to women. These stylized facts suggest that examining workers' tasks is a promising way to understand the source of the narrowing gender wage gap.

The model developed in this paper makes a clear distinction between tasks and skills. I define a task as a unit of work activity that produces output, and a skill is a worker's endowment of capabilities for performing tasks.[1] An occupation is viewed as a bundle of cognitive and motor tasks, and thus, characterized in a two-

[1]These definitions of a task and a skill follow Acemoglu and Autor (2011).

dimensional space of task complexity, using continuous indices of cognitive and motor task complexity constructed from the DOT. Workers have two different types of task-specific skills: cognitive and motor skills.[2] To produce output workers apply their skills to tasks. Skilled workers are always more productive than unskilled workers at any level of task complexity, and the productivity difference between the two increases with task complexity because skills are intensely used in complex tasks. In other words, skilled workers have an absolute advantage in all tasks and comparative advantage in complex tasks. This heterogeneity in returns to skills across tasks is the main mechanism at which workers with different skills choose different tasks.[3]

The distinction between tasks and skills are relevant not only for understanding a worker-task assignment mechanism, but also for measuring skills. To estimate workers' endowments of task-specific skills, I rely not on the current task, but on the history of past tasks, the information of which is available from the PSID. Namely, I use the sum of the task complexity indices from the previous jobs. This measure can be interpreted as task-complexity-adjusted work experience and, justified by skill acquisition through learning-by-doing. A worker which experienced complex cognitive tasks for many years, is likely to have developed more cognitive skills, Taking further advantage of the panel structure of the PSID, I take the correlated random effect approach (see Wooldridge (2009)) to address an endogeneity bias that arises from the selection into occupations based on unobserved skills. The basic idea of this approach is to put restrictions on the conditional distribution of unobserved heterogeneity given the entire occupational history. This extensive use of occupational history is an important departure from the previous contributions such as Black and Spitz-Oener (2010) and Bacolod and Blum (2010), as they do not explicitly distinguish tasks and skills and measure skills by the current tasks. The empirical evidence indicates that variables constructed from occupational history

[2]The contributions to the empirical literature on task-specific skills include, but not limited to, Poletaev and Robinson (2008), Gathmann and Schönberg (2010), and Yamaguchi (2012).

[3]Teulings (1995) and Gibbons, Katz, Lemieux, and Parent (2005) consider similar wage structures that sort workers across different jobs. Assuming an occupation as a bundle of tasks and using task complexity measures from the DOT, this paper develops a method to include about 500 occupations at the 3-digit classification level.

are strongly correlated with wages, suggesting that omitting these variable results in biased estimates.

The results from structural estimation show that, during the period of 1979-1996, men had substantially more motor skills than women, and the returns to motor skills decreased dramatically. This fall of returns to motor skills suggests that the technological change helped women catch up to men in labor market outcomes. The estimated model is then used to conduct counterfactual simulations to decompose the change in the gender wage gap during the period. The results indicate that more than 40% of the reduced gender wage gap can be explained by the fall of returns to motor skills and the rest is largely explained by an increase in women's cognitive and general skills. This main result holds even when I take into account a change in women's labor force participation pattern that is pointed out by Mulligan and Rubinstein (2008).

Related Literature

There are a few papers that attempt to explain gender wage gap based on a multi-dimensional skill model. Galor and Weil (1996) argue that gender differences in brains and brawn are important to explain the narrowing gender gap in the labor market. Welch (2000) also develops a brains-and-brawn model of earnings to explain the narrowing gender wage gap, as well as the rising male wage inequality in a single framework. These papers consider that men's skills are relatively more brawn intensive than brain, while women's skills are more brain intensive relative to brawn. Consequently, a rise in the price of brains relative to brawn explains simultaneously the rise in male wage inequality and the narrowing gender wage gap. Rendall (2010) constructs a one sector general equilibrium model in which workers possess brains and brawn, and calibrate it to the U.S. economy to examine the sources of the narrowing gender wage gap. Their models are based on the Gorman-Lancaster characteristics model of earnings, and its key feature is that the return to skills is uniform across economy.

However, Heckman and Scheinkman (1987) study conditions under which skills are uniformly priced across subsectors when worker skills cannot be unbundled and reject the hypothesis of uniform pricing of skills in the U.S. data. Their finding implies that the Gorman-Lancaster model is not the correct vehicle to study how workers are sorted across different subsectors of economy. This is an important limitation when one wishes to take a task-based approach in modeling wages or earnings, because different tasks naturally imply different subsectors. Building on Heckman and Sedlacek (1985), I overcome this limitation by constructing a task-based Roy model to explain worker assignment and wage determination when workers' skills cannot be unbundled. Unlike the Gorman-Lancaster model, returns to skills are heterogeneous across occupations, and this heterogeneity is the key mechanism that sorts workers based on their skills endowment.[4]

Recently, Beaudry and Lewis (2012) examined if computerization has reduced the gender wage gap at the city level using the census in 1980 and 2000. They find that cities that experienced faster growth in the college vs. high school graduates wage gap saw a bigger drop in the male-female wage gap. This is suggestive that computerization could be a factor that affected both wage gaps simultaneously. Beaudry and Lewis (2012)'s approach is unique in the identification strategy which relies on cross-city variations, rather than aggregate time-series variation. Because the time-series evidence could easily be spurious, their findings add more credibility to the hypothesis that computerization reduced the gender wage gap. This paper differs from Beaudry and Lewis (2012) in two respects. First, the present paper develops a model of worker assignment to tasks, which is missing from their single sector model. Second, although the identification strategy here relies on time-series variation, by taking advantage of the panel structure of the PSID this paper uses a rich set of control variables for skills in order to avoid endogeneity biases.

The rest of the paper is structured as follows. Section 2 documents the facts of the U.S. labor market from 1979 to 1996, in order to motivate the economic model. Section 3 lays out the structural model of occupational choice. Section 4 discusses the estimation strategy. Section 5 describes the data. The estimation results are presented in Section 6. Section 7 discusses robustness of the main result as well as the issues of endogenous female labor force participation decision, gender

[4] In a recent paper, Firpo, Fortin, and Lemieux (2011) develop an argument in favor of the Roy model against the Gorman-Lancaster model. Firpo, Fortin, and Lemieux (2011) find that heterogeneity in returns to skills is an important feature to understand the sources of the recent labor market polarization in the U.S.

discrimination, and international trade. Section 8 concludes.

2 U.S. Labor Market Facts in 1979-1996

In this section I show that motor-task intensive occupations suffered a large wage loss, while cognitive-task intensive occupations experienced no wage loss or even positive wage growth for the 1979-1996 period in the U.S. This difference in the wage growth pattern across occupations has the potential to explain the narrowing gender wage gap considering that the motor-task intensive occupations are male-dominated while the cognitive-task intensive occupations are not. Moreover, this can also account for the rising wage inequality among men, because majority of the male workers in the motor-task intensive occupations have less than a college education, while majority of the male workers in the cognitive-task intensive occupations are college educated. This simple descriptive analysis then motivates the structural model in the following section and clarifies the main driving force behind the estimation results for the structural model.

2.1 Data

2.1.1 Current Population Survey

In this section, I use the 1980 and 1997 CPS for the descriptive analysis because of its representativeness and large sample size. Then, I use the PSID to estimate the structural model to take advantage of its panel structure. The CPS survey years were selected to match the sample period of the PSID data used. The CPS sample consists of civilian male and female non self-employed full-time workers in the non-agricultural sector between the ages of 18 and 65. Full-time work is defined as 1,500 hours of work per year or more. Hourly wages are deflated by the 1983 PCE deflator. I exclude wages less than \$1 per hour and more than \$250 per hour from the sample. Note that wages and hours reported in the CPS, as well as in the PSID, are previous years' wages. Thus, the 1980 and 1997 surveys report wages and hours worked in 1979 and 1996, respectively. The sample restrictions imposed in this paper are comparable to Blau and Kahn (1997).

2.1.2 Dictionary of Occupational Titles

The DOT contains information on 12,099 occupations defined by worker performed tasks in each individual occupation. The U.S. Department of Labor compiled the data to provide standardized occupational information for an employment service matching job applicants with job openings. The information included in the DOT is based on the on-site observation of jobs as they are performed in diverse business establishments and, for jobs that are difficult to observe, on information obtained from professional and trade associations. On this basis, in the fourth edition of the DOT, analysts rate each occupation with respect to about 50 characteristics including aptitudes, temperaments, and interests necessary for adequate performance.

In light of the previous papers using the DOT data, this paper assumes that tasks are broadly categorized into either cognitive or motor tasks. By examining the textual definitions of the DOT variables, I select a few variables to measure each type of tasks. The DOT variables which measure cognitive task complexity consist of two worker function variables for data and people, three variables from General Educational Development for reasoning, mathematical, and language skills, three aptitude variables for intelligence, verbal, and numerical skills, and two temperament variables for influencing people and dealing with people. Motor task complexity is measured by one worker function variable for things and seven aptitude variables for motor coordination, manual dexterity, finger dexterity, eye-hand-foot coordination, spatial, form perception, and color discrimination. I summarize each set of variables into a single index of cognitive or motor task complexity by a dimension reduction technique. [5] The constructed indices are normalized such that the mean is 0.5 and the standard deviation is 0.1. As a robustness check, I also constructed the indices using a subset of the variables to more sharply define tasks, but that does not change any of the main results of the paper. Details of variable construction are available in the online appendix.

Although my task complexity measures are not identical to the routine and non-routine measures as in Autor, Levy, and Murnane (2003), complex motor tasks

[5] Multiple Correspondence Analysis is used. This method is similar to Principal Component Analysis, but can handle ordinal variables. See Greenacre (2007) for an excellent introduction to the method.

largely correspond to routine manual tasks, and complex cognitive tasks largely correspond to nonroutine analytical/interactive tasks in their measures. My motor task index does not include a physical strength measure, which might seem problematic for those who interpret the brains-and-brawn story literally, but the nuanced view of technological change emphasizes that computers replaced routine tasks while some of physically demanding tasks cannot be replaced by computers. Indeed, the physical strength measure seems to pick up nonroutine physical tasks. This is suggested by the wage regression results in Bacolod and Blum (2010) who indicate that returns to physical tasks did not decrease over time, while those to motor tasks did. These two variables are positively correlated, but need to be carefully distinguished in an empirical analysis that studies the relationship between tasks and wages.

Figure 1 plots the levels of cognitive and motor task complexity for each 1-digit occupation. Cognitive tasks of professionals and managers are the most complex, and are followed by sales, clerical, and craft workers. Cognitive task complexity is lowest for service workers, operators, and laborers. The complexity of motor tasks of craft workers is the highest among all occupations, followed by professionals, clerical workers, and operators. Service and sales workers, and laborers are involved in simple motor tasks. Managers report the lowest level of motor task complexity.

2.2 Wage Growth by Occupation and Gender Gaps

The nuanced view of technological change argues that strong complementarities exist between computers and complex cognitive tasks, while substantial substitution exists between computers and complex motor tasks. We can deduce from Figure 1, that occupations in the bottom and right regions (craft workers, operators, and laborers) should have been harmed by computerization, because they are relatively motor-task intensive occupations. Occupations in the top left region (professionals, managers, and sales) should have benefited from computerization, because they are relatively cognitive-task intensive occupations. Occupations near the diagonal (clerical and service) should have been less affected by computerization.

To examine if this prediction is consistent with the data, I calculate the changes in the composition-adjusted mean wages from 1979 to 1996 for each 1-digit oc-

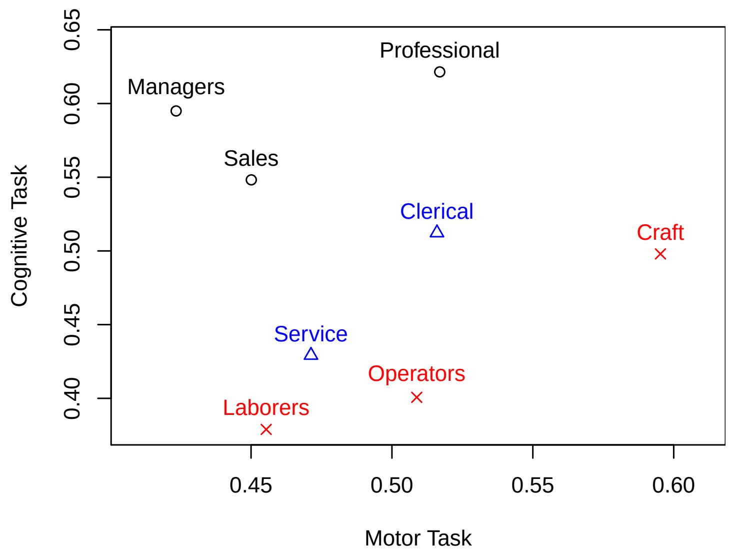


Figure 1: Occupations in the Task Space

Note: The data source is the 1971 CPS augmented by the fourth edition of the DOT. The task complexity indexes are normalized so that the mean and standard deviation for the 1971 CPS are 0.5 and 0.1, respectively.

cupation.[6] The conditional mean logwage function for 1996 is estimated by a nonparametric regression spline method using the CPS data.[7] Covariates include age, gender, five education levels (high school dropouts, high school graduates, some college, college graduates, and advanced degree), and 1-digit occupations. The composition-adjusted mean wage is calculated by applying the estimated wage equation to the 1979 CPS data.

As reported in Table 1, operators, laborers, and craft workers suffered large wage losses of 18% during this period. Clerical and service workers had modest wage losses from 8% to 5%. Wages of sales workers and managers remained almost constant, and professionals enjoyed 6% wage growth. Note that wage growth during this period did not monotonically change with the occupations' skill level. For

[6]The 1950 census occupation classification is used. Although the 1990 coding scheme is also available, the 1950 coding scheme is much more similar to the 1970 coding scheme, which is used in the PSID.

[7]See Ma, Racine, and Yang (2011).

example, craft workers experienced a large wage loss of 18%, but their average wage in 1979 is the third highest among 1-digit occupations, and immediately follows those of professionals and managers. Clerical and service workers had modest wage losses, and their wages are the first and second lowest, respectively. The wage growth patterns presented here cannot be explained by a simple model in which workers possess a single dimensional skill and its return increases over time.

These wage changes result in different consequences between men and women, and for men between high school and college graduates. First, the occupations which suffered the largest wage losses are male-dominated. In 1979, only 10% of laborers and 5% of craft workers were female. Female operators were also uncommon; their employment share was 28%. In contrast to men, the majority of women were in occupations that did not experience a significant wage loss, which resulted in a smaller wage gap between men and women. Second, majority of male workers in occupations that suffered the largest wage losses have less than a 4-year college degree. Specifically, only 3-5% of male laborers, operators, and craftsmen posses a 4-year college education. (not in the table). They are mostly concentrated in managerial, sales, and professional occupations. Hence, less educated workers tend to suffer a large wage loss, while many educated workers enjoyed a positive wage growth, resulting in a greater wage inequality between education levels. The descriptive analysis here strongly suggests that changes in returns to cognitive and motor skills are the key to understanding the driving forces behind the narrowing gender wage gap and widening education wage gap.

Another notable change during the period is that the share of female workers has increased significantly among professional, manager, and sales workers: from 41% to 53% in professionals, from 24% to 40% in managers, and from 32% to 41% in sales workers. Because these occupations are cognitive-task intensive, this change may reflect an increase in women's cognitive skills.

3 A Roy Model of Occupational Choice

The descriptive statistics in the last section suggest that occupational task is the key to understanding the relationship between the technological change and the gender

Table 1: Composition-Adjusted Wages and Share of Female Workers

	Logwage			**Fraction of Women**		
	1979	1996	Diff	1979	1996	Diff
Operatives	1.99	1.81	−0.18	0.28	0.27	−0.02
Laborer	1.93	1.75	−0.18	0.10	0.14	0.04
Craftsmen	2.25	2.07	−0.18	0.05	0.07	0.02
Service	1.70	1.62	−0.08	0.49	0.52	0.03
Clerical	1.89	1.84	−0.06	0.77	0.77	0.00
Managers	2.36	2.35	−0.01	0.24	0.40	0.16
Sales	2.11	2.10	−0.01	0.32	0.41	0.09
Professional	2.31	2.36	0.06	0.41	0.54	0.12

Note: The data source is CPS 1980 and 1997. The worker composition is fixed at the 1980 level. The variables controlled include age, gender, five education levels (high school dropouts, high school graduates, some college, college graduates, and advanced degree), and 1-digit occupations.

wage gap. Applying the task-based approach, this section develops a model of occupational choice that helps interpret the stylized facts above.

3.1 Environment

Workers have a set of skills that consists of cognitive, motor, and general skills. The skill vector of worker i in year t is denoted by $s_{it} = (s_{C,it}, s_{M,it}, s_{G,it})$ where $s_{C,it}$, $s_{M,it}$, and $s_{G,it}$ are cognitive, motor, and general skills, respectively, and take non-negative values. An occupation is defined as a bundle of tasks. Let $x_j = (x_{C,j}, x_{M,j})$ be a vector of the cognitive and motor task complexity indices that characterize the task of occupation j. The indices take non-negative values, and greater values of $x_{C,j}$ ($x_{M,j}$) imply that the cognitive (motor) task of occupation j is more complex.

Labor is the only factor of production. When occupation j is filled by a worker, she produces $q_j(s_{it})$ units of type j goods. Assume, for simplicity, that technology is constant over time in this section. The aggregate output produced by all workers in occupation j is denoted by $Q_{jt} = \sum_{i \in I_j} q_j(s_{it})$, where I_j is the set of workers whose occupation is j. This is used as an intermediate input in the production of final consumption goods and it is priced P_{jt} in the intermediate input market.

3.2 Wage Structure

Wages are paid according to the value of marginal product of labor

$$w_{ijt} = P_{jt} q_j(s_{it}). \tag{1}$$

Assuming that the output of worker i in occupation j is given by a Cobb-Douglas production function, I specify the logwage of worker i in occupation j at time t as

$$\begin{aligned}
\ln w_{ijt} &= \ln P_{jt} + \ln \alpha_j + \beta_{C,j} \ln s_{C,it} + \beta_{M,j} \ln s_{M,it} + \ln s_{G,it} && (2) \\
&\equiv \Pi_{jt} + \beta_{C,j} \ln s_{C,it} + \beta_{M,j} \ln s_{M,it} + \ln s_{G,it}. && (3)
\end{aligned}$$

Note that the intercept Π_{jt} and returns to skills ($\beta_{C,j}$ and $\beta_{M,j}$) vary across occupations and that occupations are characterized by tasks. Hence, these occupation-specific parameters can be replaced by functions of tasks,

$$\begin{aligned}
\Pi_{jt} &= p_t(x_j) && (4) \\
\beta_{C,j} &= b_C(x_{C,j}) && (5) \\
\beta_{M,j} &= b_M(x_{M,j}). && (6)
\end{aligned}$$

Cognitive and motor skills (s_C and s_M) are referred to as task-specific skills, because log of their marginal product of labor varies across occupations depending on the complexity of the task performed. In contrast, the general skill s_G is general in the sense that its log-marginal product of labor is constant across all occupations. This heterogeneity in returns to skills is an important feature of a Roy model. Depending on the workers' skill endowment, best-paying jobs are different for different workers, which gives rise to self-selection into occupations. This is the key difference from the Gorman-Lancaster characteristics type of model in which returns to skills are uniform across subsectors of the economy. With uniform returns to skills, workers are indifferent between jobs, and no occupational choice problem exists.

In the standard Roy model, an occupation is treated as a distinct category, and the occupation-specific parameters vary arbitrarily across occupations. A major limitation with this standard approach is that the number of variables and parameters increase with the number of occupations in the model. This is particularly problematic when a researcher wishes to use a list of finely defined 3-digit occupations in the U.S. census classification system, which covers about 500 occupations. Even though estimation itself is straightforward in a linear model, it may be hard to learn from so many parameter estimates how and why returns to skills are different across occupations. Even worse, when hundreds of free parameters exist in the model, the precision of estimates may be too low to make any definitive conclusions. For a nonlinear model (e.g. a structural dynamic programming model), computational burden for estimation may be enormous with hundreds of free parameters. Many empirical researchers avoid this problem by aggregating occupations into a small number of broadly defined occupation groups (e.g. the 1-digit classification system). The drawback of the aggregation is the loss of rich information available at the narrowly defined occupation level.

This limitation of the standard Roy model approach can be overcome in the task-based approach. Any differences across occupations such as return to skills are explained by the differences in tasks. In addition, computation is greatly simplified because the number of variables does not change with the number of occupations in the model, but with the number of tasks that characterize occupations. As long as the dimension of the task vector that characterizes occupations stays low, model estimation is tractable even when millions of different occupations are in the model.

How should the occupation-specific parameters vary across occupations? Consider a simple task. It can be properly done regardless of worker skills, although skilled workers may produce more. In contrast, for a complex task, worker's skills matter very much: bad workers will likely fail and good workers succeed. Skills are more used and contribute to productivity, when the corresponding tasks are complex. Assuming differentiability, I can formulate this idea as

$$\frac{\partial p_t}{\partial x_k} < 0 \tag{7}$$

$$\frac{\partial b_k}{\partial x_k} > 0 \tag{8}$$

for $k \in \{C, M\}$. Figure 2 illustrates how logwage changes with a worker's task-specific skill between simple and complex tasks. In both simple and complex tasks, logwage increases with skills, but the slope of the logwage schedule is steeper for the complex task. Also note that the intercept of the logwage schedule is lower for the complex task. What the figure indicates is that when the task is simple, the productivity difference between skilled and unskilled workers is small. In contrast, when the task is complex, output is sensitive to worker skills and the productivity difference between skilled and unskilled workers is amplified. Hence, in Figure 2, all workers with skills less than s^* earn more in the simple task than in the complex task, while workers with skills more than s^* earn more in the complex task than in the simple task.[8]

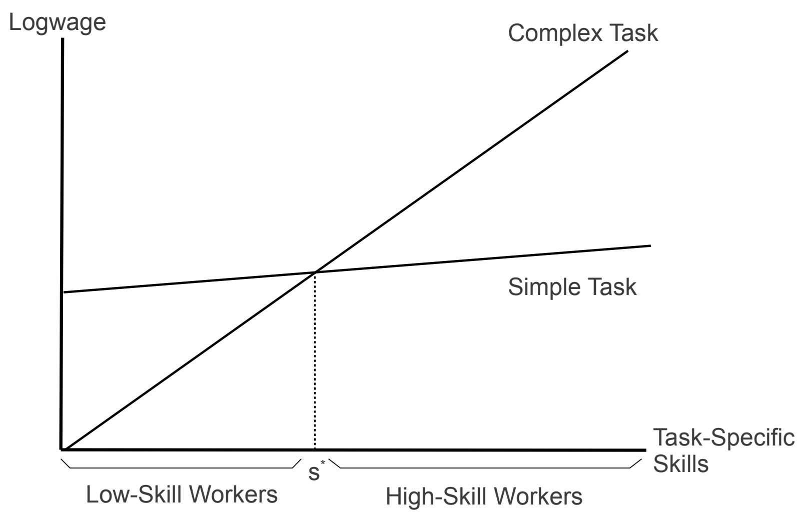


Figure 2: Occupational Sorting Based on Task-Specific Skill

3.3 Skill Growth

Workers enter the labor market with a vector of initial skills endowment $s_{i\underline{t}_i}$ where $\underline{t}_i$ is the year when worker i entered the labor market. Task-specific and general skills

[8]Yamaguchi (2012) takes the approach to approximate occupation-specific parameters by functions of tasks, but does not show how heterogeneity in returns to skills sort workers across tasks. A technical, but important difference between the present model and that in Yamaguchi (2012) is that the present model incorporates general skills. Without general skills, the estimated model does not present the trade-off between the intercept and the slope, which is the key driving force of worker sorting.

grow over time according to the following skill growth equations,

$$\ln s_{k,it} - \ln s_{k,it-1} = g_{k,j}(e_{it}) = g_k(e_{it}, x_{k,j}) \text{ for } k \in \{C, M\} \tag{9}$$

$$\ln s_{G,it} - \ln s_{G,it-1} = g_G(e_{it}) \tag{10}$$

where e_{it} is general work experience and occupation-specific function $g_{k,j}$ is replaced by a function of tasks $g_k(x_{k,j})$, like the wage equation parameters in Equations (4)-(6). Assume that skills remain unchanged when one does not work.

The skill growth rates decrease with experience, which generates a concave experience-skill profile, and ultimately, a concave experience-wage profile. The growth rates of task-specific skills vary across tasks, which allows for heterogeneous profiles of skill and wage over time. In the estimated model, the task-specific skill growth rates increase with task complexity, suggesting skill acquisition through learning-by-doing. In other words, by doing a complex task, a worker can develop relevant skills more quickly than when she does a simple task.

3.4 Individual Utility Maximization

Workers supply labor inelastically and do not borrow or lend money, implying consumption equals wages $c_{it} = w_{ijt}$. I further assume that the utility for consumption is given by the logarithmic function. In each period while in the labor market, a worker chooses an occupation to maximize her present value of lifetime utility. This is the only choice made by workers in this model. The decision horizon is infinite and no uncertainty exists. These last assumptions are for expositional purpose only and are not essential for the substance of the argument below.

The value function of a worker with skill s_{it} is

$$V_t(s_{it}) = \max_{x_j} \ln w_t(x_j, s_{it}) + \rho V_{t+1}(s_{it+1}) \tag{11}$$

where ρ is a discount factor. The constraints for the worker's maximization problem are given by the skill growth equations (9) and (10). Note that choosing an occupation is equivalent to choosing a bundle of tasks.

To characterize a worker's optimal occupational choice easily, I assume that there is a continuum of occupations so that workers can choose any task vector x_j in a continuous space. Assuming an interior solution, the first order condition for optimality is given by differentiating the value function with respect to the index for task k,

$$\begin{aligned} & \frac{\partial \ln w_{ijt}}{\partial x_k} + \rho \frac{\partial V_{t+1}(s_{it+1})}{\partial x_k} \\ = \quad & \frac{\partial p_t}{\partial x_k} + \frac{\partial b_k}{\partial x_k} \ln s_{k,it} + \rho \frac{\partial V_{t+1}(s_{it+1})}{\partial s_{k,it+1}} \frac{\partial s_{k,it+1}}{\partial x_k} = 0. \end{aligned} \tag{12}$$

The first two terms capture the marginal wage return to the task, and the third term captures the marginal effect of the task on the future utility generated through skill growth. When conditions (7) and (8) are satisfied, a worker faces a trade-off between the intercept and the slope as illustrated in Figure 2. In addition, she also takes into account the skill learning opportunities, as captured by the last term of Equation (12).

4 Estimation Strategy

4.1 Model Specification

4.1.1 Wage Equation

The model laid out in the previous section captures the relationship between tasks, skills, and wages. Although the main focus of the paper is the role of tasks and task-specific skills in changing the gender wage gap, other factors, particularly a decline of union coverage rates, might have played an important role as well. Blanchflower and Bryson (2004) finds that workers make at least 15% higher wages when their jobs are covered by a union contract. In the PSID, 34.3% of men were covered by a union contract in 1979, but the rate decreased to 20.4% by 1996 (Table 2). On the other hand, the union coverage rate for women has been around 18% in both years. Given that many blue collar jobs are motor-task intensive and covered by a union contract, the large wage decline of motor-task intensive jobs in Section 2.2

might reflect the decline of union coverage rates, rather than the decline in returns to motor skills. To address this concern, I include the union coverage in the wage equation and specify it as

$$\ln w_{ijt} \quad = \quad \Pi_{jt} + \beta_{C,j} \ln s_{C,it} + \beta_{M,j} \ln s_{M,it} + \ln s_{G,it} + \beta_{U,t} u_{it}, \tag{13}$$

where u_{it} is an indicator variable that takes one if individual i's job is covered by a union contract and takes zero otherwise. The parameter $\beta_{U,t}$ is union wage premium and it varies with time. While it is technically feasible to allow for the time-varying parameter to change arbitrarily across years, I cannot estimate it precisely due to the sample size being small. As an accommodation, the time-varying wage premium is approximated by a piecewise-linear function

$$\beta_{U,t} \quad = \quad \beta_{U,0} + \beta_{U,1} t_{79} + \beta_{U,2} t_{89}, \tag{14}$$

where $t_{79} = (t - 1979)$, $t_{89} = (t - 1989) \cdot I(t \geq 1989)$. $I(\cdot)$ is an indicator function that takes the value one if the condition in the parenthesis is satisfied and zero otherwise.

As discussed above, occupation-specific parameters are replaced by functions of tasks (see Equations 4-6). The intercept Π_{jt} is specified as a quadratic function for tasks

$$\begin{aligned} \Pi_{jt} &= p_t(x) \\ &= \pi_{0,t} + \pi_{1,t} x_{C,j} + \pi_{2,t} x_{M,j} + \pi_{3,t} x_{C,j}^2 + \pi_{4,t} x_{M,j}^2 + \pi_{5,t} x_{C,j} x_{M,j}. \end{aligned} \tag{15}$$

Because the function $p_t(x)$ is time-varying, so are the parameters π. These time-varying parameters π are approximated by a piecewise-linear function. For example, the parameter $\pi_{0,t}$ is given by

$$\pi_{0,t} \quad = \quad \pi_0 + \pi_{0,79} t_{79} + \pi_{0,89} t_{89}. \tag{16}$$

In Section 3, technology is assumed to be constant over time so that the returns to skills ($\beta_{C,j}$ and $\beta_{M,j}$) are time-invariant. When estimating the model, however, I allow for them to change over time, in order to observe the effect of technological change. Assuming that technological change has a secular trend, I specify the functions for returns to skills as

$$\begin{aligned}\beta_{k,j,t} &= b_{k,t}(x_{k,j}) \\ &= (\beta_{k,0}+\beta_{k,1}t_{79})+(\beta_{k,2}+\beta_{k,3}t_{79})x_{k,j}. \qquad (17)\end{aligned}$$

Modeling the technological change by a linear trend term is a common approach in the literature (see Katz and Murphy (1992), for example).

4.1.2 Skill Equation

The initial skill endowment is specified as

$$s_{k,i\underline{t}_i} = \exp(\gamma'_{k,0}d_i+\sigma_{k,i}+\varepsilon_{k,i\underline{t}_i}), \qquad (18)$$

where $\underline{t}_i$ is the year when worker i enters the labor market. d_i is a vector of worker's characteristics that are invariant after the entry into the labor market, such as education, race, and gender.[9] $\sigma_{k,i}$ is a time-invariant unobserved component, and $\varepsilon_{k,i\underline{t}_i}$ is a time-varying unobserved component.

The skill growth Equations (9) and (10) together with Equation (18) imply that log skills in year t can be written as

$$\begin{aligned}\ln s_{k,it} &= \gamma'_{k,0}d_i+\gamma_{k,1}e_{it}+\gamma_{k,2}e_{it}^2+\gamma_{k,3}\sum_{\tau=\underline{t}_i}^{t-1}x_{k,ij\tau}+\sigma_{k,i}+\varepsilon_{k,it} \quad k\in\{C,M\} \qquad (19)\\ \ln s_{G,it} &= \gamma'_{G,0}d_i+\gamma_{G,1}e_{it}+\gamma_{G,2}e_{it}^2+\sigma_{G,i}+\varepsilon_{G,it}. \qquad (20)\end{aligned}$$

Note that none of the parameters in the skill equations are time-varying. This restriction implies that workers in different years are comparable if their observed characteristics and occupational histories are the same. The fourth term in Equa-

[9]Many papers on gender wage gap do not include a gender dummy in their wage equations, but doing so raises concern over omitted variable bias. Fortin (2008) extensively discusses this issue and supports the use of a gender dummy variable.

tion (19) is the sum of the task indices of the previous jobs. This term captures the skill component acquired through learning-by-doing. Because this term gives rise to a heterogeneous skill growth profile conditional on occupational experiences, this specification allows for heterogeneous wage growth profiles.

Notice that neither demeaning nor first-differencing eliminates the time-invariant unobserved skills $\sigma_{k,i}$, because they are interacted with the task index x. The quasi-differencing method used by Gibbons, Katz, Lemieux, and Parent (2005) does not work either, because there is more than one time-invariant unobserved variable.

I take the correlated random effect approach (see Wooldridge (2009)) to address the endogeneity bias caused by the correlation between unobserved skills σ and tasks x. The basic idea of the correlated random effect approach is to put restrictions on the conditional distribution of unobserved heterogeneity given the entire history of the covariates. Specifically, the time-invariant components of the unobserved task-specific skills are modeled as

$$\sigma_{k,i} = \gamma_{k,4}\bar{x}_{k,i} + \gamma_{k,5}\bar{u}_i + \gamma_{k,6}\bar{x}_{k,i}\bar{u}_i + \theta_{k,i} \text{ for } k \in \{C,M\} \quad (21)$$

$$\sigma_{G,i} = \gamma_{G,3}\bar{u}_i + \theta_{G,i} \quad (22)$$

$$E(\theta_{k,i}|x_{ijt},\bar{x}_i,\bar{u}_i,e_{it},d_i) = 0 \text{ for } k \in \{C,M,G\}, \quad (23)$$

where $\bar{x}_i$ and $\bar{u}_i$ are time-averages of the task indices and union coverage over years observed in the data, respectively.

Motivated by the worker assignment mechanism outlined in Section 3.4, I include the variable $\bar{x}_i$ to control for the time-invariant unobserved skills $\sigma_{k,i}$. In the model, workers who have high time-invariant unobserved cognitive (motor) skills choose complex cognitive (motor) tasks persistently throughout their careers, which is captured by the time-average of the task indices $\bar{x}_{k,i}$. As well, workers with high motor skills tend to take jobs that are covered by a union contract. To allow for the correlation between union coverage and worker skills, I include the variable $\bar{u}_i$ as an additional control for the time-invariant skills.

Finally, the time-varying components of the unobserved skills satisfy the conditional mean independence assumption,

$$E(\varepsilon_{k,it}|x_{ijt},\bar{x}_i,\bar{u}_i,e_{it},d_i) \;=\; 0 \text{ for } k\in\{C,M,G\}. \tag{24}$$

4.2 Estimation by Nonlinear Least Squares

The parameters of the wage equation (13) and the skill equations (19)-(20) in Section 4.1 are estimated by the nonlinear least squares. Estimation involves a single-equation because the wage equation incorporates the skill equations. Nonlinearity arises from the restriction that parameters of the skill equations are time-invariant, while those of the wage equation are time-varying. Because skills do not have a natural unit, a normalization restriction must be imposed on either the return-to-skill equation (17) or skill equation (19). Without loss of generality, I impose that $\beta_{k,2}=1$ in equation (17). Under the assumptions (23) and (24) the parameters are consistently identified.

Note that there are no restrictions imposed as implied by the optimal occupational choice (e.g. Equation (12)). Such restrictions improve efficiency of the estimator if correct, but they bias estimates if incorrect. In fact, the true occupational choice may be more complicated than that characterized by the first order condition (12). This is true, for example, when preference for tasks and uncertainty affect workers' decisions. Similarly, this approach allows me to estimate the parameters of the wage and skill equations without modeling a labor force participation process, which can be very complicated for women. The approach taken in this paper is robust to different models of occupational choice and labor force participation. Another benefit of this less complex approach is that it makes the estimation process and the driving force of the result relatively transparent.[10]

[10] Yamaguchi (2012) structurally estimates both the wage and occupational choice equations derived from his task-based Roy model by the Kalman filter using the data from NLSY79. The estimation strategy taken in this paper differs from this previous work in three ways. First, the present paper estimates only the wage equation for robustness. Second, this paper does not assume a parametric distribution for unobserved skills, while the previous work assumes normality to apply the Kalman filter. Third, the econometric model in Yamaguchi (2012) allows for serially correlated unobserved skills, but not for the permanent unobserved skills.

4.3 Identification

The key identifying assumption is selection on observables: a broader set of control variables captures the heterogeneity amongst workers sufficiently well and takes care of the endogeneity bias effectively. I consider two components of unobserved skills: time-invariant and time-varying. The time-invariant component is largely controlled by the correlated random effect approach detailed in Section 4.1.2. The control variable, the time-average of task indices $\bar{x}$, is motivated by the theoretical argument over worker assignment to tasks in Section 3.4. I also argue that the time-varying component of unobserved skills is controlled for by including a rich set of observed variables in the skill equation (19). In particular, the key variable is the sum of the task indices of the past jobs, which allows me to account for heterogeneity in wage growth profiles.

A possible alternative approach to the selection bias is the instrumental variable method. For example, Gould (2002) and Fletcher and Sindelar (2009) instrument occupations using the occupations of the worker's father, because fathers affect occupational preference of children. Fletcher and Sindelar (2009) in their study of the causal effect of occupations on health use the fractions of blue-collar workers in a given state to measure availability of blue-collar and white-collar jobs. The fact that a substantial proportion of jobs in Michigan are blue collar increases the likelihood that a new entrant will start working in a blue collar job.

However, I do not instrument the task indices for occupations by these variables for two reasons. First, these instruments may not satisfy an exclusion restriction in the present context. Second, my control variables for skills seem to work well, and father's occupation and local labor market conditions do not provide much additional identification power. I run the instrumental variable first-stage regressions to see how strongly the instruments are correlated with the task indices. Without my key control variables constructed from workers' occupational history, the instruments are strongly correlated with task indices. Once the control variables are included, the instruments are no longer strong. This exercise suggests, but by no means proves, that the additional skill control variables effectively take care of the endogeneity problem at least to the extent that the previous papers do using instrumental variables approach. Details of this exercise are available in the online appendix.

Another important issue on identification is what features of the data allow one to identify how an observed characteristic such as education can be associated with three different types of skills. That can be identified by variations of the wage return to the worker characteristic (e.g. education) across different tasks. Suppose that education increases cognitive skills. Then, the wage gap between high school and college educated workers increases with cognitive task complexity, because returns to cognitive skills increase with task complexity. Similarly, if men possess more motor skills than women, the gender wage gap increases with motor task complexity. The component of the wage gap invariant to tasks is associated with general skills. This argument is elaborated in the online appendix.

5 Data: PSID

5.1 Sample Restrictions and Variable Definitions

The PSID is a nationally representative household panel survey that began in 1968. To study the evolutions of tasks, skills, and wages, I draw a sample of household heads and wives[11] who worked full-time (1,500 hours a year or more) from 1979 to 1996. I select these survey years, because all the variables are available, and more importantly, we observe that the wage inequality increased and the gender wage gap narrowed rapidly during this period. I restrict the sample of individuals to be between 18 and 65 years old. The sample does not include self-employed and agricultural workers. The sample restrictions are comparable to those used in the literature such as in Blau and Kahn (1997).[12]

Hourly wages are calculated by dividing labor income by hours of work, and are deflated by the 1983 PCE Index. Note that hours of work and labor income indicated are for the previous year of the survey, similar to the CPS. The number on the years

[11]In the PSID, a man is by construction a household head for a married or cohabiting couple. A women can be a household head in a single household.

[12]Blau and Kahn (1997) also extensively examine the issue of sample attrition in the PSID by comparing various statistics with the CPS. They find that the reported hourly wages in the PSID tend to be higher than the CPS, but do not find evidence of a significant attrition bias in other statistics. Most importantly, they find that changes in gender wage gap are very similar in the two data sets.

of experience is not available for every survey year. For years when experience is not recorded, it is imputed using hours of work observation. Occupations in the PSID are coded using the 1970 census scheme. This coding is used to merge the PSID sample with the task indices from DOT. Details of variable definitions are outlined in the online appendix.

5.2 Summary Statistics of the Sample

Table 2 reports the means of selected labor market outcomes for men and women in 1979 and 1996. The mean log hourly wage exhibits well-known patterns. Men's wages were higher than women's by 48.1% in 1979 and 29.0% in 1996. From 1996 to 1979, the gender wage gap decreased by 19.1 percentage points. Both men's and women's cognitive task complexity indices grew over the period, while their motor task complexity indices decreased. These patterns exhibit the shift from motor to cognitive tasks, and are consistent with the nuanced view of technological change. Furthermore, both men and women became better educated over time and achieved that at about the same rate in the sample period. The gender gap in the work experience has significantly decreased from 6.5 years to 4 years. The union coverage rate for men was 34.3% in 1979, but dropped to 20.4% by 1996. Women's union coverage rates remained stable around 18% in both years.

Table 2: Differences Between Men and Women in 1979 and 1996

	1979			**1996**			
	Men	Women	Diff	Men	Women	Diff	D-in-D
Logwage	2.405	1.924	0.481	2.400	2.109	0.290	−0.191
Cognitive Task	0.518	0.514	0.005	0.529	0.543	−0.014	−0.018
Motor Task	0.511	0.499	0.013	0.501	0.482	0.020	0.007
White	0.896	0.861	0.034	0.896	0.863	0.033	−0.002
Education	12.633	12.456	0.177	13.634	13.520	0.114	−0.063
Experience	18.294	11.836	6.458	19.092	15.223	3.869	−2.589
Union Coverage	0.343	0.182	0.161	0.204	0.177	0.027	−0.134

Note: The source is the PSID in 1979-1996. Wages are deflated by 1983 PCE Index. The sample includes household heads and wives who worked full-time (1,500 hours a year or more). Those who are younger than 18 or older than 65 are excluded from the sample. Self-employed and agricultural workers are also not in the sample. The PSID sample weights are applied.

6 Empirical Results

This section presents the main result of the paper. In Subsection 6.1, I show that the skill measures based on occupational history are strongly correlated with wages. Subsection 6.2 shows how returns to skills vary across occupations and change from 1979 to 1996. Subsection 6.3 presents estimated differences in skill endowments between men and women. In Subsection 6.4, I decompose the changes in the gender wage gap using a version of the Oaxaca-Blinder decomposition method.

6.1 Parameter Estimates

In this subsection I restrict the discussion to a few parameter estimates concerned with skills. All the parameter estimates are reported in the online appendix.

To control for worker skills, I take a correlated random effect approach and include in the skill equations the averages of task complexity indices $\bar{x}$ and union dummies $\bar{u}$ and their interaction (See Equations 21 and 22). I test the null hypothesis that these variables are uncorrelated with unobserved skills σ_k for each type of skill. The test statistics and p-values are reported in rows 1-3 of Table 3. The null hypotheses are soundly rejected for cognitive and general skills, while it is marginally rejected for motor skills at the 10% significance level (p-value is 0.082). I also test the null hypothesis that all of the additional variables used to control for the correlated random effects are zero. This is soundly rejected as well. Therefore, the test results here indicate that these additional variables are useful in controlling for time-invariant worker skills.

Another set of key variables used to estimate task-specific skills are sums of task complexity indices for the past jobs. They are included in the skill equations to account for differences in time-varying components of task-specific skills across individuals. They are statistically significant at 1% level for both cognitive and motor skills, and the asymptotic t-values are 6.714 and 2.833, respectively (see Table 12 in the online appendix). Omitting these variables results in biased parameter estimates even if a correlated random effect approach is taken, because it does not take care of time-varying components of worker skills.

All the variables discussed in this subsection are not included in the wage regressions in the previous papers. The significance test results, however, indicate that omitting them produces biased estimates of a wage regression with occupation dummies and/or task indices.

Table 3: Testing Correlated Random Effects

	Wald Statistic	p-Value
(1) Cognitive Skill	85.386	0.000
(2) Motor Skill	6.705	0.082
(3) General Skill	75.793	0.000
(4) All Skills	686.904	0.000

Note: The null hypothesis for row (1) is that $\gamma_{C,4} = \gamma_{C,5} = \gamma_{C,6} = 0$ in Equation (21). The null hypothesis for row (2) is that $\gamma_{M,4} = \gamma_{M,5} = \gamma_{M,6} = 0$ in Equation (21). The null hypothesis for row (3) is that $\gamma_{G,4} = 0$ in Equation (22). The null hypothesis for row (4) is that all of these parameters are jointly zero.

6.2 Wage Structure

6.2.1 Heterogeneity in Returns to Skills Across Tasks

Heterogeneity in returns to skills across tasks is the main driver of worker-task assignment, as discussed in Section 3. The key feature of the assignment mechanism is the trade-off between the intercept and the slope of the wage schedule in Figure 2. On the one hand, a simple task offers a high guaranteed wage, but the wage changes little with skills. On the other hand, a complex task offers a low guaranteed wage, but the wage quickly increases with skills. Given these wage schedules, and workers' self-selection, low skill workers take a simple task and high skill workers take a complex task. In estimating the model, I do not impose a restriction that generates such a trade-off. Nevertheless, in the estimated model a trade-off between the intercept and the slope emerges.

Figure 3 illustrates the estimated wage schedules for 1979.[13] The horizontal axes show normalized task-specific skills. They are normalized so that mean and standard deviation of the skills are zero and one for all male and female workers in 1979. The vertical axes show normalized logwage. It is normalized so that mean is

[13]A figure for the estimated wage schedule for 1996 is available upon request.

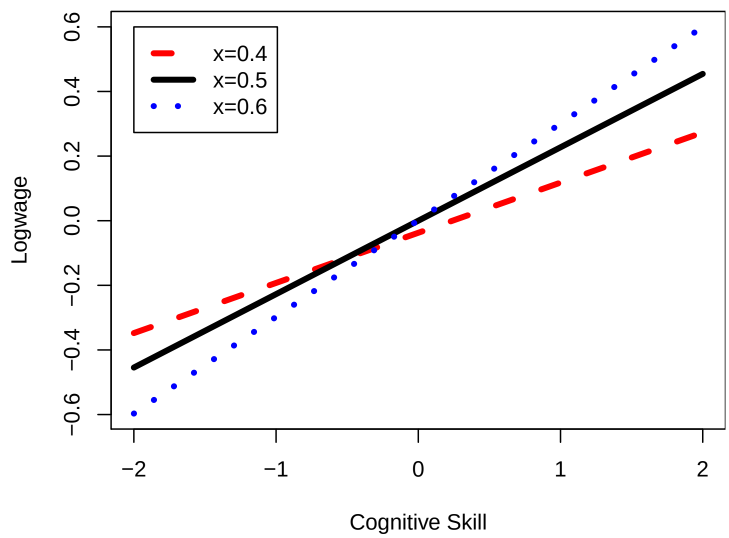
zero for those whose skills and occupations are average, i.e. the skill is zero and task is 0.5 in the graphs. The top panel of Figure 3 displays the wage schedule along the dimension of cognitive tasks and skills, while the bottom panel represents the wage schedule for the motor tasks and skills. For both dimensions, a trade-off between the intercept and the slope is evident.

Identical workers are paid differently depending on tasks. For example, a worker with cognitive skills one standard deviation higher than the average earns 18% higher wage by taking a complex task ($x = 0.6$) than by taking a simple task ($x = 0.4$).[14] Similarly, a worker with cognitive skills one standard deviation lower than the average earns 11% higher wage by taking a simple task than by taking a complex task. Wage differences are also found across different motor tasks, although they are smaller than those across cognitive tasks. For example, a worker with motor skills one standard deviation higher than the average earns 6% higher wage by taking a complex task than by taking a simple task. A worker with motor skills one standard deviation lower than the average earns 1% higher wage by taking a simple task than by taking a complex task.

6.2.2 Changes in Average Returns to Skills

To provide a general picture of the evolution of returns to skills, I calculate the average of the returns to skills over all workers in a given year using the PSID sampling weights. The average returns to skills change over time for two reasons. First, workers undertake different tasks over time. If workers complete more complex tasks over time, the returns to skills increase over time, because complex tasks utilize their skills more intensely, resulting in a higher rate of return. This effect of occupational composition can be obtained by fixing the parameters for the returns to skills at the 1979 level. Then, the difference in the returns to skills between 1979 and 1996 under this restriction reflects the effect of changes in occupational composition. Second, technological change directly affects the returns to skills, which is captured by changes in the parameters over time. I calculate this effect by fixing the occupational composition in 1979 with parameters being allowed to change over

[14] Remember that the task index is normalized such that mean is 0.5 and standard deviation is 0.1.



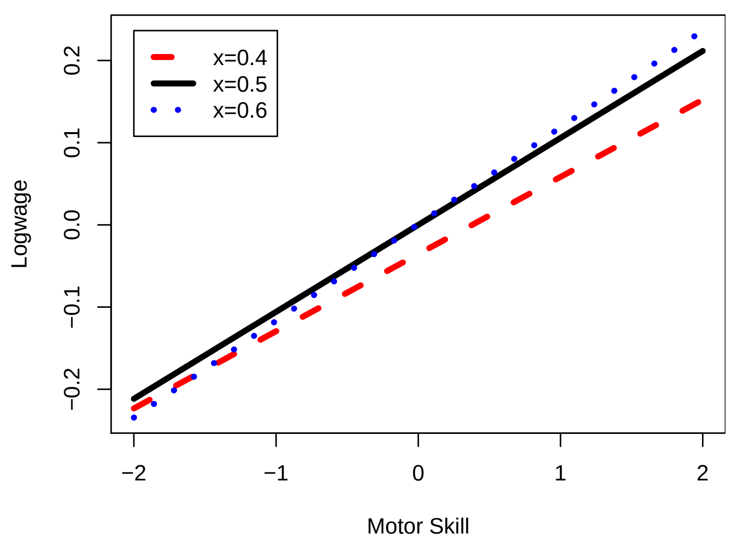


Figure 3: Estimated Wage Schedules in 1979

Note: Estimated wage schedules in 1979 are presented for three different tasks. The horizontal axis shows skills normalized so that the mean is zero and the standard deviation is one. The vertical axis shows logwage normalized so that the average worker (her skill level is zero) earns zero at the average job ($x = 0.5$).

time, which isolates the effect of the technological change.

Table 4 summarizes the estimates for the changes in returns to skills. From 1979 to 1996, the return to cognitive skills increased by 13.5%, while those to motor skills decreased by 68.3%. It was the technological change during this period that was largely responsible for these changes in returns to skills. The technological change increased the returns to cognitive skills by 7.8% and decreased the returns to motor skills by 66.7%. Changes in occupational composition also contributed to the changes in returns to skills, but to a lesser extent. They increased the returns to cognitive skills by 5.7% and decreased the returns to motor skills by only 1.6%. These patterns are consistent with the theory by Autor, Levy, and Murnane (2003) and descriptive statistics shown in Section 2.2.

Table 4: Changes in Returns to Skills

	Estimates	Std. Error
Tech Change		
%Δ Returns to Cognitive Skill	7.8	5.3
%Δ Returns to Motor Skill	−66.7	9.9
Occ. Composition		
%Δ Returns to Cognitive Skill	5.7	0.6
%Δ Returns to Motor Skill	−1.6	0.6
Total		
%Δ Returns to Cognitive Skill	13.5	5.4
%Δ Returns to Motor Skill	−68.3	10.0

6.3 Skill Endowments

Table 5 reports estimated skill gaps between men and women. Because no natural metric for skills exists, the skill gaps for both years are measured in logwage by multiplying the skill gaps and the returns to skills for an average task ($x = 0.5$) in 1979. The gaps are calculated by subtracting the average women's skills from the average men's skills. Hence, positive numbers indicate that men have more skills than women, and vice versa. Relative to the motor skill gap, the cognitive skill gap between men and women was small. In 1979, men had more cognitive skills than women, and the difference was equivalent to 1.2% higher wage. In 1996, women's cognitive skills exceeded men's, and the gap was worth 2.6% higher wage for women. The difference in each year is neither statistically nor economically significant. A significant gap in motor skills, however, existed between men and women: men have more motor skills than women, which resulted in a 12.4-13.0% higher wage for men between 1979 and 1996. Lastly, I find a large gender gap in general skills, worth around 25-29% higher wage for men.

In the previous literature, no gender difference in cognitive skills and a significant gender difference in motor skills are often assumed, but not estimated.(See Galor and Weil (1996) and Rendall (2010)). Black and Spitz-Oener (2010) and Bacolod and Blum (2010) measure the gender difference in these skills by the task indices alone. However, they do not find a difference large enough to lead to a significant gender wage gap. This paper takes one step further and estimates the gender gap in skill endowments. I find the estimates are intuitive, and confirm the assumptions made by Galor and Weil (1996) and Rendall (2010).

Table 5: Skill Gaps Between Men and Women

	1979		**1996**	
	Estimates	Std. Error	Estimates	Std. Error
Cognitive Skill	0.012	0.015	−0.026	0.015
Motor Skill	0.130	0.023	0.124	0.022
General Skill	0.285	0.027	0.245	0.026

Note: Measured in logwage by multiplying the skill gaps and the returns to skills for an average task ($x = 0.5$) in 1979. Positive numbers indicate that men have more skills than women, and vice versa.

6.4 Wage Gap Decomposition

One of the key findings so far is that men have more motor skills than women, and the technological change reduced returns to motor skills. This implies that the technological change is responsible for the reduced gender wage gap from 1979 to 1996. In this subsection I estimate the effect of the technological change on the gender wage gap, along with contributions of the other factors.

I decompose changes in the gender wage gap using a method similar to Oaxaca-Blinder decomposition. Namely, changes in the gap are decomposed into (1) the wage structure effect that reflects changes in parameter values and (2) the composition effect that reflects the changes in tasks and skills. To derive the composition effect, I fix the parameters (i.e., the wage structure) at either the 1979 or 1996 level and calculate counterfactual wage gaps. The difference between the predicted wage gap of the estimated model and the composition effect identifies the wage structure effect. The decomposition exercise is carried out as follows. The gender wage gap in year t ,G_t, is measured by mean logwage difference between men and women and given by

$$G_t = G(\Theta_t,\, F_t)$$

where Θ_t is a set of parameters in year t, and F_t is a distribution function in year t for task, skill, and gender. The change in the gender wage gap from 1979 and 1996 is $\Delta G = G(\Theta_{96}, F_{96}) - G(\Theta_{79}, F_{79})$, which can be decomposed into the two components in two different ways:

$$\Delta G = \underset{\text{"Wage Structure Effect"}}{[G(\Theta_{96}, F_{96}) - G(\Theta_{79}, F_{96})]} + \underset{\text{"Composition Effect"}}{[G(\Theta_{79}, F_{96}) - G(\Theta_{79}, F_{79})]} \tag{25}$$

or

$$\Delta G = \underset{\text{"Composition Effect"}}{[G(\Theta_{96}, F_{96}) - G(\Theta_{96}, F_{79})]} + \underset{\text{"Wage Structure Effect"}}{[G(\Theta_{96}, F_{79}) - G(\Theta_{79}, F_{79})]} . \tag{26}$$

Notice that the logwage is linearly separable in the cognitive, motor, and general skill components. Hence, composition and wage structure effects are further decomposed into these different skill components.[15]

Table 6 presents the results for the gender logwage gap decomposition using Equations (25) and (26). From 1979 to 1996, the observed gender logwage gap has decreased by 0.187 log points. Out of 0.187 log points, changes in returns to skills and tasks, and the union premium (wage structure effects) account for 0.080-0.086

[15]Although it is technically feasible, I do not decompose into the effects of skills and those of tasks, because tasks are endogenously determined. Given the theoretical model, changes of tasks are interpreted as consequences of changes in skills.

Table 6: Decomposition of Changes in Gender Logwage Gap

	Base Year: 1979		Base Year: 1996	
	Estimate	Std. Error	Estimate	Std. Error
Wage Structure Effect				
Output Price	0.003	0.009	−0.001	0.005
Returns to Cognitive Skill	−0.006	0.007	0.003	0.005
Returns to Motor Skill	−0.084	0.010	−0.087	0.010
Union Premium	0.001	0.000	0.005	0.003
Composition Effect				
Cognitive Task & Skill	−0.058	0.006	−0.035	0.007
Motor Task & Skill	0.002	0.004	−0.007	0.003
Interaction of Cognitive & Motor Tasks	0.010	0.003	−0.006	0.003
General Skill	−0.041	0.004	−0.041	0.004
Union Coverage	−0.014	0.001	−0.018	0.002
Residuals	−0.004	0.009	−0.004	0.009
Total	−0.191	0.027	−0.191	0.027

Note: Base year refers to the year in which the parameters are fixed in calculating the composition effect. Namely, the first two columns use Equation (25), and the second two columns use Equation (26).

change in skill endowments, while tasks and union coverages (composition effects) account for 0.101-0.107 of the change. The remaining 0.004 stay as unexplained by the model.

The most notable feature in the table is that the drop in returns to motor skills accounts for about half of the narrowing gender wage gap: 0.084-0.087 log points. This result is along the same line as the empirical analysis in Section 2.2 in which motor-task intensive jobs suffer a large wage loss and are male-dominated. Devaluation of motor skills hurt men, but not women, resulting in a narrowing gender wage gap. Changes in returns to cognitive skills and tasks affected the gender wage gap little, because the gender gap in cognitive skills was modest in the first place.

Another important point is that women's growth in general and cognitive skills greatly narrowed the gender wage gap: women's cognitive skills growth accounts for 0.035-0.058 log points, and their general skills growth accounts for 0.041 log points. During the period examined, women became more educated and experienced, and undertook more complex cognitive tasks than they used to, resulting in larger cognitive and general skill endowments. Again, this result is along the line of the observed increase in the share of female workers in managerial and professional occupations, as seen in Section 2.2.

De-unionization does not appear to have a large effect on gender wage gap. Union premium was 0.106 and fairly stable over time (see Table 9), and its change had very little effect on the gender wage gap. The decrease in men's union coverage rate from 34% to 20% from 1979 to 1996 (see Table 2) accounts for only 0.014 log points.

Previous papers find that the wage structure effect is small or leads to a widening gender wage gap. Blau and Kahn (1997) find that changes in the wage structure should have widened the gender wage gap, because they measure skills by education and experience, and the returns to those variables have increased. Bacolod and Blum (2010) include occupational task variables in their wage regression and find that the wage structure effect narrowed the gender wage gap by only 0.02 log points. Their results indicate that the composition effect is the major factor in explaining the narrowing gender wage gap. In contrast, this paper finds a large wage structure effect: the decrease in the rate of return to motor skills has narrowed the gender wage gap significantly. The main methodological difference of this paper from the previous contributions is in taking the estimation one step further by allowing for heterogeneous returns to skills across tasks and including a broader set of control variables for task-specific skills.

Although the main focus of this paper is the gender wage gap, the theory also predicts a rise in male wage inequality across education categories. To see if the technological change also accounts for the wage gap among males, I examine skill gaps between men with high school education only and and college graduates and then decompose the change of their wage gap during the same period in a similar fashion as above. The following summarizes the results for men. Details of this exercise are available in the online appendix.

The estimates show that college educated men have more cognitive skills than their high school educated counterparts. The gap translates into 36% and 42% higher wages in 1979 and 1996, respectively. High school educated men have slightly more motor skills than college educated men, reflecting the fact that the former tend to occupy motor-task intensive jobs. The motor skill gap is worth only 6% higher wage. No significant difference in general skills exists.

From 1979 to 1996, the observed logwage gap between high school and college educated men has decreased by 0.237 log points. Out of 0.237 log points, changes in returns to skills and tasks, and the union premium (wage structure effects) account for 0.100-0.107, while changes in skill endowments, tasks and the union coverage (composition effects) account for 0.123-0.131. The remaining 0.007 log points are unexplained by the model. Most of the wage structure effect comes from changes in returns to task-specific skills, and the effects of changes in output price and the union premium have a modest effect. Faster growth of cognitive and general skills for college educated men than high school educated men also significantly widened the wage gap.

7 Discussion

7.1 Selection into Labor Force

Mulligan and Rubinstein (2008) find that the rise in returns to skills, which changed the labor force participation patterns of women, ultimately changed the observed gender wage gap. During the 1970's, unskilled women participated in the labor market, while skilled women remained at home. In the 1980's and 90's, returns to skills rose, increasing the opportunity cost of staying at home for skilled women. Consequently, more and more skilled women started participating in the labor market. They claim that this compositional change of female labor force accounts for the change in the observed gender wage gap even if no change in the wage structure exists.

Although this paper does not model labor force participation, it addresses the composition change in female labor force by including a rich set of variables to measure skills. In the CPS data used by Mulligan and Rubinstein (2008), actual work experience, and more importantly, workers' occupational history are not available. These are key variables to measure women's skills, and the estimation results reported in Table 5 indicate that the model indeed captures women's skill upgrading over time. To further check if women's skill upgrading not captured by the current model exists, I estimate the model allowing for cohort effects. This change does not affect the main result.[16] The decomposition exercise in Section 6.4 shows that the composition change is an important source of the narrowing gender wage gap, but it is far from the whole explanation. The decrease in returns to motor skills also played an important role in reducing the gender wage gap.

7.2 Gender Discrimination

In the model, wages are equal to the value of the marginal product of labor, and the gender wage gap is due to differences in skills and tasks. Gender discrimination may potentially be picked up by a female dummy variable in the skill functions (19) and (20). However, the estimates of task-specific skill endowments do not suffer from a bias arising from potential gender discrimination, unless the level of discrimination is correlated with task complexity. Discussions in Section 4.3 and in the online appendix explain how the gender difference in task-specific skills is identified. In the data, the gender wage gap increases with motor task complexity, and this positive correlation between motor task complexity and the gender wage gap is the identification source of the gender gap in motor skills. If gender discrimination exists but it is not correlated with task complexity, discrimination is absorbed by general skills.

Most theories of gender discrimination do not suggest a correlation between tasks and discrimination. An exception is the "glass ceiling" theory - that women are kept from rising to the upper rungs of the corporate ladder - which implies that women are more strongly discriminated against as the cognitive tasks become more complex (e.g. managerial positions). This effect may bias women's cognitive skill endowments downward, which implies women had more cognitive skills than men during the period examined. If this is the case, there may be a stronger role for the technological change in accounting for the change in the gender wage gap, because returns to cognitive skills increased during the period. However, the "glass ceiling" theory may not be as relevant in the present context, because it is about executive

[16] See the online appendix for details of this exercise.

positions.

Note that women's growth of general skills is driven by better education and more experience. This is true even if the estimates of the general skill endowments are biased due to gender discrimination, because the coefficient for a female dummy is time-invariant in the skill production function. Hence, once a broad set of worker characteristics is controlled for, a change in gender discrimination does not appear as an important source of the narrowing gender wage gap.[17]

7.3 International Trade

This paper argues that the technological change is the source of the changes in returns to skills. However, trade with developing countries may also hurt unskilled workers. In the Heckscher-Ohlin model, trade with developing countries raises the demand for skill-intensive goods made in the U.S. This change in demand ultimately increases returns to skills in the U.S. through a price increase of the skill-intensive goods, the effect known as the Stolper-Samuelson theorem. However, Lawrence and Slaughter (1993) and Sachs and Shatz (1994) find that the relative price of skill-intensive goods did not increase over the period of increasing inequality. Another evidence in conflict with the trade theory's is that returns to skills in developing countries also increased. This is opposite to the theoretical predictions. Furthermore, another evidence in support of the technology view and against the trade view is that the share of skilled workers increased within industries, while the trade theory predicts it would have remained intact. Moreover, Berman, Bound, and Griliches (1994) find that the skill-biased technological change is pervasive across developed countries, implying that the technological change increases returns to skills even in an open economy.[18]

[17]Of course, it is possible that the changes in worker characteristics are results of a change in gender discrimination.

[18]There is an on-going debate about how off-shoring affects the U.S. labor market. Among others, Firpo, Fortin, and Lemieux (2011) find that off-shoring contributes to wage inequality in the U.S, but that occurred since 2000s. Because the period of study of this paper is from 1979 to 1996, international trade and off-shoring seem to have little effect on the changes in returns to skills.

8 Conclusion

Based on the task-based approach, this paper constructs a Roy model of occupational choice in which workers possess cognitive and motor skills and occupations are characterized by cognitive and motor tasks. The key feature of the model is the heterogeneity in returns to skills across occupations that gives rise to self-selection into occupations. The model is used as a guide to how a wage equation should be formulated and motivates the way to measure skills.

The empirical results indicate that men have significantly more motor skills than women, while only a small difference in cognitive skills between genders exists. Between 1979 and 1996, the returns to motor skills dropped dramatically, while those to cognitive skills increased modestly. This suggests that technological change is responsible for the narrowing gender wage gap. In particular, the significant drop in returns to motor skills accounts for more than 40% of the narrowing in the gap. Increases in women's cognitive and general skills also significantly narrowed the gender wage gap. This technological change also accounts for the large portion of the rise in male wage inequality across education categories.

Although I provide evidence that taking occupational choice and labor force participation as exogenous, conditional on the broad set of control variables, does not largely bias the main results, incorporating these features in the model is a promising direction for future research. Changes in returns to skills should have affected workers' skill investment as well as occupational choice and labor force participation decisions. Studying these changes in worker behavior is an important step toward a thorough understanding of how technological change has reshaped the labor market.

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A Details on the Data (For Online Publication)

A.1 DOT

In the DOT, many characteristics are measured by a multi-point scale and have detailed definitions. For example, the variable DATA measures by integers from 0 to 6 the complexity of tasks in relation to information, knowledge, and conceptions. Tasks at the lowest level of complexity involve judging the readily observable characteristics of data. Examples include sorting hats according to color and size specified, comparing invoices of incoming articles with the actual number and weight of articles, and so on. Tasks at the intermediate level of complexity involve compiling information. Examples include summarizing details of transactions, collecting, classifying, and recording data, and receiving customer complaints to record and file them for future processing. Tasks at the highest level of complexity involve integrating analysis of data to discover facts and developing the knowledge of concepts for interpretations. Examples include formulating hypotheses and experimental designs, writing critical reviews of art for publication, and conducting research. Other tasks such as operating machines or equipment are also evaluated in a similar manner. Some tasks are measured by a binary variable that takes the value one if the occupation involves the task and zero otherwise.

Table 7: DOT Variables for Cognitive Task Complexity Index

Variable	No of Categories/Levels
Worker Function	
DATA	7
PEOPLE	9
General Educational Development	
reasoning	6
mathematics	6
language	6
Aptitude	
intelligence	4
verbal	5
numerical	5
Temperament	
influencing people	2
dealing with people	2

Table 8: DOT Variables for Motor Task Complexity Index

Variable	No of Categories/Levels
Worker Function	
THINGS	8
Aptitude	
motor coordination	5
finger dexterity	5
manual dexterity	5
eye-hand-foot coordination	5
spatial	5
form perception	5
color discrimination	5

Tables 7 and 8 show variables that measure cognitive and motor task complexity. They are highly correlated within the task group, and thus the information can be summarized by a single index using Multiple Correspondence Analysis (MCA). Correspondence analysis is a generalized principal component analysis tailored for the analysis of qualitative data. MCA is an extension of correspondence analysis which allows one to analyze the pattern of relationships of several categorical dependent variables. In short, MCA is a dimension reduction technique for categorical variables. There are 10 categorical variables for the cognitive task complexity index and 8 categorical variables for the motor task complexity index. These variables are converted into 52 and 43 indicator variables, respectively. In MCA, variation of the data is called inertia, which is the sum of chi-square distances to the centroid. In calculating inertia, I account for off-diagonal subtables of the Burt matrix only.

I apply the MCA to the April 1971 CPS, augmented by the fourth edition of the DOT.[19] This is the only data that contains the 1970 census occupation code, the DOT occupation code, and the DOT variables, which allows for linking the DOT variables and the census occupation code. The task complexity indices constructed by MCA account for 50% and 39% of the inertia of the 1971 CPS sample, respectively. The resulting indices at the individual level are aggregated into the level of the 1970 census occupation by taking the mean for each of the 1970 census 3-digit occupations using the sampling weights so that they can be merged with the PSID. The indices are normalized so that the mean is 0.5 and the standard deviation is 0.1

[19]The data file is available at the ICPSR website (http://dx.doi.org/10.3886/ICPSR07845.v2).

for the working individuals in the 1971 augmented CPS.

A.2 PSID

The following is the definitions of the variables taken from the PSID.

Education Education is reported in the PSID in 1968, 1975, and 1985 for existing heads[20] of households, and every year for the new entrants into the sample only. When education is missing, I first use education reported in the survey prior to the year when education is missing. Then, if necessary, I use the education reported in the survey after the year when education is missing.

Demographic Variables Age, gender, and race are used in this paper. Wife's race is not reported between 1968 and 1984. I assume wife's race is the same as that of her husband during this period. If more than one race is reported throughout the survey years, the most often reported answer is used.

Wages Hourly wages are calculated by dividing total labor earnings by hours worked. They are then deflated by the1983 PCE Index. Hourly wages less than $1 or more than $250 are treated as missing.

Hours Worked When missing, I impute hours of work by taking an average of those in the previous and next years. The imputed values are used to determine whether one works full-time or not. A full-time work consists of 1,500 hours of work in a year. This variable is subsequently used to construct experience and task indices. The imputed values are not used to calculate hourly wages.

Experience Experience is reported for 1974, 1975, 1976, 1985, and years when a household is interviewed for the first time. For all other years, experience is imputed, using the indicators for full-time work and experience reported in the earlier

[20] In the PSID, a man is by construction a household head for a married or cohabiting couple. A women can be a household head in a single household.

survey closest to the year when experience is missing. For example, to impute experience in 1980, I add years of full-time work from 1976 to 1979 to experience reported in 1976. Similarly, experience in 1990 is calculated by adding years of full-time work from 1985 to 1989 to experience reported in 1990.

Occupation and Industry For years between 1968 and 1980, I use the occupation and industry codes from the retrospective supplemental data files. From 1981 on, the code reported in each survey year is used.

Union Coverage An indicator for whether the job is covered by a union contract is available in all years from 1979 to 1996 for both household heads and wives.

Task Index The task indices constructed from the DOT are merged with the PSID sample using the 1970 Census 3-digit occupation code. When occupation is missing, but those in the previous and next years are available, the task index is imputed by taking an average of those. When occupation is missing, but that in the previous (next) year is available and the individual does not work full-time in the next (previous) year, the task index in the current year is assumed to be the same as that in the previous (next) year. No imputation is conducted in all other cases.

Cumulated Task Index Because the PSID does not include the whole occupational history since the entry into the labor market, the cumulative task index is imputed as follows. I first run a fixed-effect regression of the task index on experience and its square. Here, I assume that individuals have a common slope for the profile of task index and experience, but they have different intercepts. The individual intercept is given by an average of residuals from the fixed-effect regression. The missing values are imputed using the estimated task-experience profile with heterogeneous intercepts.

B Parameter Estimates (For Online Publication)

The following tables report the estimates of the structural parameters of the model.

Table 9: Effect of Union Coverage

	Estimate	Std. Error
Union Coverage	0.106	0.011
Union Coverage × t_{79}	0.002	0.001
Union Coverage × t_{89}	−0.001	0.002

Note: The parameter estimates for Equation (14) are reported. $t_{79} = (t - 1979)$ and $t_{89} = (t - 1989) \cdot I(t \geq 1989)$ where $I(\cdot)$ is an indicator function that takes the value one if the condition in the parenthesis is satisfied and zero otherwise.

Table 10: Output Price Function

	Estimate	Std. Error
Intercept	0.879	0.212
t_{79}	0.028	0.026
t_{89}	0.084	0.053
COG	−1.765	0.532
COG × t_{79}	0.002	0.070
COG × t_{89}	−0.197	0.149
COG-sq	−1.796	0.690
COG-sq × t_{79}	−0.086	0.077
COG-sq × t_{89}	0.147	0.128
MTR	2.734	0.500
MTR × t_{79}	−0.142	0.065
MTR × t_{89}	−0.046	0.134
MTR-sq	−1.730	0.482
MTR-sq × t_{79}	0.035	0.061
MTR-sq × t_{89}	0.052	0.119
COG × MTR	−2.140	0.586
COG × MTR × t_{79}	0.217	0.077
COG × MTR × t_{89}	−0.024	0.167

Note: The parameter estimates for Equations (15) and (16) are reported. COG and MTR are abbreviations for cognitive and motor, respectively. $t_{79} = (t - 1979)$ and $t_{89} = (t - 1989) \cdot I(t \geq 1989)$ where $I(\cdot)$ is an indicator function that takes the value one if the condition in the parenthesis is satisfied and zero otherwise.

Table 11: Returns to Skills

	Estimate	Std. Error
Cognitive Skill		
Intercept	-0.184	0.037
t_{79}	0.004	0.008
COG	1.000	
COG $\times$ t_{79}	-0.001	0.004
Motor Skill		
Intercept	0.388	0.309
t_{79}	-0.009	0.029
MTR	1.000	
MTR $\times$ t_{79}	-0.031	0.025

Note: The parameter estimates for Equation (17) are reported. COG and MTR are abbreviations for cognitive and motor skills, respectively. $t_{79} = (t - 1979)$ and $t_{89} = (t - 1989) \cdot I(t \geq 1989)$ where $I(\cdot)$ is an indicator function that takes the value one if the condition in the parenthesis is satisfied and zero otherwise.

Table 12: Skill Equations

	Estimate	Std. Error
Cognitive Skill		
Woman	0.089	0.047
White	−0.069	0.049
Education	0.070	0.012
Experience	0.034	0.007
Experience^2/100	−0.114	0.016
Sum of COG	0.047	0.007
Ave. of COG	6.780	0.752
Ave. of Union	1.575	0.289
Ave. of COG × Ave. of Union	−3.532	0.527
Motor Skill		
Woman	−0.116	0.041
White	−0.009	0.016
Education	−0.009	0.006
Experience	0.013	0.006
Experience^2/100	−0.050	0.017
Sum of MTR	0.017	0.006
Ave. of MTR	0.487	0.192
Ave. of Union	0.091	0.114
Ave. of MTR × Ave. of Union	−0.149	0.198
General Skill		
Woman	−0.197	0.027
White	0.104	0.020
Education	0.017	0.006
Experience	0.002	0.004
Experience^2/100	0.014	0.010
Ave. of Union	0.295	0.034

Note: The parameter estimates for Equations (19)-(22) are reported. COG and MTR are abbreviations for cognitive and motor skills, respectively.

C Comparison Between High School and College Educated Men (For Online Publication)

The following tables report statistics and estimates for high school and college educated men. See the footnotes for details.

Table 13: Differences Between High School and College Educated Men in 1979 and 1996

	1979			1996			
	College	HS	Diff	College	HS	Diff	D-in-D
Logwage	2.655	2.360	0.295	2.750	2.218	0.532	0.237
Cognitive Task	0.611	0.489	0.122	0.604	0.482	0.122	0.000
Motor Task	0.483	0.529	−0.046	0.471	0.522	−0.051	−0.005
White	0.956	0.877	0.079	0.945	0.874	0.071	−0.008
Education	15.950	12.000	3.950	16.281	12.000	4.281	0.331
Experience	15.752	18.039	−2.288	18.977	18.998	−0.021	2.267
Union Coverage	0.140	0.428	−0.288	0.115	0.281	−0.166	0.121

Note: The source is the PSID 1979-1996. Wages are deflated by 1983 PCE Index. The sample includes household heads and wives who worked full-time (1,500 hours a year or more). Self-employed workers and those who are younger than 18 or older than 65 are excluded from the sample. Sample weights are applied.

Table 14: Skill Gap Between High School and College Educated Men

	1979		1996	
	Estimates	Std. Error	Estimates	Std. Error
Cognitive Skill	0.358	0.022	0.415	0.025
Motor Skill	−0.060	0.021	−0.062	0.022
General Skill	−0.018	0.026	0.029	0.027

Note: Measured in logwage by multiplying the skill gaps and the returns to skills for an average task ($x = 0.5$) in 1979. Positive numbers indicate that college educated men have more skills than high school educated men, and vice versa.

Table 15: Decomposition of Changes in Male Logwage Gap

	Base Year: 1979		Base Year: 1996	
	Estimate	Std. Error	Estimate	Std. Error
Wage Structure Effect				
Output Price	−0.010	0.084	−0.007	0.086
Returns to Cognitive Skill	0.079	0.090	0.075	0.089
Returns to Motor Skill	0.043	0.015	0.041	0.014
Union Premium	−0.005	0.003	−0.009	0.005
Composition Effect				
Cognitive Task & Skill	0.064	0.005	0.070	0.005
Motor Task & Skill	−0.008	0.004	0.002	0.002
Interaction of Cognitive & Motor Tasks	0.007	0.002	−0.005	0.002
General Skill	0.047	0.004	0.047	0.004
Union Coverage	0.013	0.001	0.017	0.001
Residuals	0.007	0.010	0.007	0.010
Total	0.237	0.046	0.237	0.046

Note: Base year refers to the year in which the parameters are fixed in calculating the composition effect. Namely, the first two columns use Equation (25), and the second two columns use Equation (26).

D Identification Strategy (For Online Publication)

D.1 First Stage Regression for Instrumental Variables

I run the instrumental variable first-stage regressions to see how strongly instruments used in previous papers are correlated with the task indices. The dependent variables are the cognitive and motor task indices, and the instruments used include 9 dummies for father's occupation, the state-level employment shares for 8 occupations (1-digit), and the state-level unemployment rate. Along with these instruments, I include two sets of covariates. In model 1, I include variables that are routinely used in wage regressions: education, experience, experience-squared, and dummies for whites and females. In model 2, in addition to the covariates in model 1, I include the sum of the task indices for the past jobs, the time-average of the task indices, the time-average of the union status, and the interaction of the last two. These additional variables in model 2 are not used by previous papers, and I expect them to control for worker heterogeneity in this model regression. I run the first-stage regressions for models 1 and 2 by pooling the PSID sample, eliminating observations with missing variables.

Table 16 reports F-statistics. Staiger and Stock (1997) suggest a rule-of-thumb that the F-statistic must be greater than 10 to reject the null hypothesis of weak instruments in cross-section data with homoskedastic error terms when one instrument exists in the model. In model 1, the instrumental variables are strongly correlated with the cognitive task index with the F-statistic being 67.245. The F-statistic for the motor task index is at 10.221. However, in model 2 with the skill control variables, the instruments are no longer as strong. For the cognitive task index, the F-statistic is only 9.393, and it is 2.633 for the motor task index.

Table 16: Significance Test for Instruments for Task Indices

	DF	F-statistic
Model 1		
Cognitive Task	18	67.245
Motor Task	18	10.221
Model 2		
Cognitive Task	18	9.393
Motor Task	18	2.633

Source: PSID 1979-1996. Sample size is 61,311.
Note: IVs include 9 dummies for father's occupation, the state-level employment shares for 8 occupations (1-digit), and the state-level unemployment rate. In model 1, I also include education, experience, experience-squared, and dummies for whites and females. In model 2, in addition to the covariates in model 1, I include the sum of the task indexes for the past jobs, the time-average of the task indexes, and its squared.

D.2 Identifying Source for Skill Endowments

The model allows me to estimate how an observed characteristic such as education can be associated with three different types of skills: cognitive, motor, and general. This subsection explains which features of the data allow me to identify the relationship between a single variable and three different types of skills.

To simplify the discussion, consider $t = 1979$ and drop the time subscript. Denote conditioning variables by X_i. The conditional mean logwage is given by

$$
\begin{aligned}
& E(\ln w_{ij}|X_i) \\
= \; & \pi_0 + \pi_1 x_{C,j} + \pi_2 x_{M,j} + \pi_3 x_{C,j}^2 + \pi_4 x_{M,j}^2 + \pi_t x_{C,j} x_{M,j} + \\
& (\beta_{C,0} + \beta_{C,2} x_{C,j}) \cdot (\gamma_{C,0} d_i + \gamma_{C,1} e_i + \gamma_{C,2} e_i^2 + \gamma_{C,3} \sum_{\tau=\underline{t}_i}^{t-1} x_{C,ij\tau} + \gamma_{C,4} \bar{x}_{C,i} + \gamma_{C,5} \bar{u}_i + \gamma_{C,6} \bar{x}_{C,i} \bar{u}_i) \\
& (\beta_{M,0} + \beta_{M,2} x_{C,j}) \cdot (\gamma_{M,0} d_i + \gamma_{M,1} e_{it} + \gamma_{M,2} e_{it}^2 + \gamma_{M,3} \sum_{\tau=\underline{t}_i}^{t-1} x_{M,ij\tau} + \gamma_{M,4} \bar{x}_{M,i} + \gamma_{M,5} \bar{u}_i + \gamma_{M,6} \bar{x}_{M,i} \bar{u}_i) \\
& + (\gamma_{G,0} d_i + \gamma_{G,1} e_{it} + \gamma_{G,2} e_{it}^2 + \gamma_{G,3} \bar{u}_i) + \beta_U u_i, \qquad (27)
\end{aligned}
$$

where the second line corresponds to Π_j (the intercept of the production function), the third line is the product of returns to cognitive skill and the skill endowments, the fourth line is the product of those of motor skills, and the fifth line includes general skills and union coverage.

Identification of the parameters for the occupation-specific intercept, general skills, and union coverage (π, γ_G, and β_U, respectively) is straightforward. The parameters in the function for returns to skills β and those in the skill equations γ are identified up to scale. One of the parameters for the returns to skills or the skill function must be fixed for each of the task-specific skills. Without loss of generality, I normalize the parameters by setting $\beta_{k,2} = 1$.

The parameters for the task-specific skill production function (γ_k for $k \in \{C, M\}$) are identified using the variation of the product of the current task complexity index and the worker characteristics d, because

$$
\beta_{k,2} \gamma_{k,0} \;=\; \frac{\partial E(\ln w_{ij}|X_i)}{\partial x_{k,j} \partial d_i} \qquad (28)
$$

and $\beta_{k,2} = 1$. Hence, variation in returns to worker characteristics d_i across tasks x allows me to identify how a single characteristic such as education can be associated with three different types of skills.

To understand the intuition behind this result, consider the identification of task-specific skill differences across education. In the data, the wage gap between high school graduates and college graduates increases with the cognitive task complexity, conditional on the set of the control variables. Note that the worker assignment to tasks can be considered exogenous given the set of the control variables under the identification assumptions discussed in the previous section. This varying wage gap between the education levels across tasks implies that college graduates possess more cognitive skills than high school graduates, all else being equal. At any level of complexity of the cognitive task, college graduates earn more than high school graduates because they possess more cognitive skills. Moreover, their advantage in cognitive skills is more strongly pronounced in a complex cognitive task, because cognitive skills are intensely utilized in a complex task. Similarly, I need to examine how the education wage gap changes with the motor task complexity, in order to identify how education is associated with motor skills. The education wage gap that does not vary across tasks identifies how education is associated with general skills.

E Selection into Labor Force (For Online Publication)

I attempt to account for changes in the skill composition of workers and so allow for cohort effects in the general skills function by including a birth year variable and its interaction with a female dummy. These additional variables capture changes in conditional mean unobserved skills, given full-time labor force participation, which may include the selection effect pointed out by Mulligan and Rubinstein (2008) and the pure cohort effects. Note that these effects are identified separately for men and women. Cohort effects could be included in the task-specific skill functions as well, but the standard errors are too large to interpret the result in a meaningful way.

Table 17 reports the Oaxaca-Blinder decomposition result under the augmented specification. There is no significant difference from the results for the preferred specification in Table 6. In the augmented model, changes in cognitive and general skills account for 0.063-0.090 out of 0.191, which is not very different to the estimates in the preferred specification of 0.076-0.099. The results indicate that changes in selection and cohort effects are largely taken care of by including the additional skill measures.

Table 17: Decomposition of Changes in Gender Logwage Gap (Accounting for Cohort Effects)

	Base Year: 1979		**Base Year: 1996**	
	Estimate	Std. Error	Estimate	Std. Error
Wage Structure Effect				
Output Price	0.014	0.007	−0.011	0.004
Returns to Cognitive Skill	−0.018	0.006	0.012	0.004
Returns to Motor Skill	−0.092	0.010	−0.097	0.010
Union Premium	0.001	0.000	0.005	0.003
Composition Effect				
Cognitive Task & Skill	−0.058	0.007	−0.031	0.007
Motor Task & Skill	0.000	0.006	−0.010	0.004
Interaction of Cognitive & Motor Tasks	0.009	0.003	−0.007	0.003
General Skill	−0.032	0.011	−0.032	0.011
Union Coverage	−0.014	0.001	−0.018	0.002
Residuals	−0.002	0.011	−0.002	0.011
Total	−0.191	0.027	−0.191	0.027

Note: Base year refers to the year in which the parameters are fixed in calculating the composition effect. Namely, the first two columns use Equation (25), and the second two columns use Equation (26).