Putting Tasks to the Test: Human Capital, Job Tasks, and Wages

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Using original, representative survey data, we document that analytical, routine, and manual job tasks can be measured with high validity, vary substantially within and between occupations, are significantly related to workers' characteristics, and are robustly predictive of wage differences between occupations and among workers in the same occupation. We offer a conceptual framework that makes explicit the causal links between human capital endowments, occupational assignment, job tasks, and wages, which motivate a Roy model of the allocation of workers to occupations. We offer two simple tests of the model's gross predictions for the relationship between tasks and wages, both of which receive qualified empirical support.

Introduction

Contemporary analysis of the economic value of skill in the labor market is rooted in Becker's (1964) human capital model. A central insight of the Becker framework is that skill can be treated as a durable investment good that is acquired (i.e., purchased) in part by attending school or engaging in

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on-the-job training. Building from this logic, empirical analysis of the market price of skill, starting with Mincer (1974), uses investment measures, such as years of schooling and experience, as proxies for skill. The human capital model has been highly successful in explaining both the level of the return to education and its evolution over time (Goldin and Katz 2008). This model is not directly informative about the demand side of the human capital market, however. In particular, it is silent on what factors determine the skills that employers demand, why these skills are required, and how these skill requirements have changed over time. To answer these foundational questions requires a conceptual framework that links the tasks and activities that workers perform on the job to the skills needed to carry out these activities.

Recent literature attempts to supply this conceptual apparatus by using a "task framework" to analyze job skill requirements (Autor, Levy, and Murnane 2003). The simple idea of this approach is to classify jobs according to their core task requirements—that is, the main activities that workers must accomplish in their work—and then consider the set of formal and informal skills required to carry out these tasks. The task approach potentially offers a microfoundation for linking the aggregate demand for skill in the labor market—a primitive in the human capital model—to the specific skill demands of given job activities.

The task approach has found application in several recent strands of work. Autor et al. (2003) study the link between evolving technology, changes in job task requirements, and shifts in the demand for workers of different levels of education. Their primary hypothesis is that workplace computerization leads to the automation of a large set of "middle education" (i.e., high school or some college) routine cognitive and manual tasks, such as bookkeeping, clerical work, and repetitive production tasks. Job tasks in these occupations are readily automated because they follow precise, well-understood procedures or "routines"—that lend themselves to codification in computer software. A key implication of the Autor et al. (2003) hypothesis is that the well-documented hollowing out (or "polarization") of the occupational distribution of employment in numerous advanced countries is in part attributable to computerization.

Subsequent work by Autor, Katz, and Kearney (2006, 2008), Spitz-Oener (2006), Bartel, Ichniowski, and Shaw (2007), Felstead et al. (2007), Goos and Manning (2007), Smith (2008), Dustmann, Ludsteck, and Schönberg (2009), Antonczyk, DeLeire, and Fitzenberger (2010), Black and Spitz-Oener (2010), Gathmann and Schönberg (2010), Firpo, Fortin, and Lemieux (2011), Goos, Manning, and Salomons (2012), and Autor and Dorn (forthcoming), along with many other recent studies too numerous to list here, have used the "task approach" to explore links between technological change, changes in task inputs, and shifts in wage structure.[1]

[1] Goos and Manning use the term "polarization" in a 2003 working paper. Acemoglu (1999), Goos and Manning (2003, 2007), Autor et al. (2006, 2008), Spitz-

Recent work in the immigration literature also employs a task approach. Papers by Cortes (2008) and Peri and Sparber (2009) compare the job task assignments of equally educated native and immigrant workers.[2] Several recent studies consider the effect of international offshoring on US employment. In these studies, the unit of analysis is job tasks rather than jobs per se. Antràs, Garicano, and Rossi-Hansberg (2006) and Grossman and Rossi-Hansberg (2008) develop theoretical models of international offshoring built upon the notion that routine job tasks are more suitable for offshoring than nonroutine job tasks. Empirical papers by Blinder (2007) and Jensen and Kletzer (2010) analyze the task content of US jobs to assess their potential for international offshoring.

While these examples highlight the potential value of job tasks as an organizing framework, the task approach faces two significant challenges. The first is conceptual. Research using the task approach has not to date made explicit the economic mapping between tasks, which are characteristics of jobs, and human capital, which is a characteristic of workers. This disjuncture between tasks and human capital is particularly relevant to the analysis of the wage "returns" to job tasks, as we discuss below.[3]

The second challenge is measurement. The primary research data sets used for studying employment and earnings provide rough measures of workers' human capital, such as education, potential experience, gender, race, and place of birth, but essentially no information on their job tasks. To overcome this limitation, researchers typically impute task require-

Oener (2006), Smith (2008), Dustmann et al. (2009), Goos et al. (2012) , and Autor and Dorn (forthcoming) present evidence that employment polarization has occurred during the last two decades in the United Kingdom, United States, and in 14 of 16 Western European countries for which consistent data are available for 1993–2006. Black and Spitz-Oener (2010) consider implications of this phenomenon for demand for female labor. Bartel et al. (2007) present plant-level evidence on the impact of computerization on work organization and productivity in the valve manufacturing industry. Firpo et al. (2011) explore the degree to which the polarization of US wages during the 1990s (i.e., the relative growth of earnings at high and low wage percentiles) can be explained by changes in task prices, growth of offshoring, and changes in labor market institutions.

[2] In related work, Black and Spitz-Oener (2010) point to differences between males and females in job task specialization as a factor contributing to the closing of the gender gap in the United States and Germany.

[3] Heckman and Scheinkman (1987) provide the canonical theoretical treatment of the pricing of skill "bundles" in the labor market in a setting where workers cannot unbundle their skills. A general result of their model is that, due to bundling, skills will not generally be uniformly priced across sectors except under specialized circumstances. Two recent papers that offer explicit links between human capital returns and task prices are Acemoglu and Autor (2011) and Firpo et al. (2011). The first offers an assignment framework that characterizes the equilibrium assignment of skills to tasks and the determination of wages when different skill groups differ in their comparative advantage across task categories. The second considers how a change in task prices affects wage inequality in a static Roy model setting where returns to tasks are assumed to differ by occupation.

ments to person-level observations using data from the US Department of Labor's *Dictionary of Occupational Titles* (DOT) and its successor, the Occupational Information Network (O*Net). Both data sets offer representative measures of job requirements in detailed occupation, but their limitations for task measurement are substantial.[4] Most significantly, both DOT and O*Net provide information on job characteristics only at the level of occupations, not workers. This makes analysis of within-occupation heterogeneity in task demands and its relationship to earnings infeasible.[5] We present evidence below both that job tasks differ among workers within an occupation and that this variation is an important determinant of earnings.

The current paper provides an exploratory effort to confront both of the limitations above: a lack of conceptual structure for analyzing the wage "returns" to tasks and a lack of data for analyzing the person-level relationship between tasks, education, and wages. The first section offers a simple conceptual framework for interpreting the relationship between job tasks and wages. We argue that the familiar logic of the Mincerian wage regression, used to estimate the "return to education," does not carry over to estimating the "returns to tasks." Distinct from durable investments such as education, job tasks are not fixed worker attributes; workers can modify their task inputs by self-selecting into particular jobs according to comparative advantage and reallocate their labor input among tasks when the market value of tasks changes. These assumptions motivate the use of a Roy (1951) self-selection framework to analyze the relationship between tasks and wages. We show that a simple, multidimensional Roy model implies some testable restrictions on the relationship between "task returns" within and between occupations and that these implications are distinct from the Mincerian model.[6]

The second goal of our paper is to explore the value added of task measurement at the person level for analyzing job content and wage determination. For this analysis, we collected new data on the job activities of a representative sample of US workers across a variety of task domains, including cognitive, interpersonal, and physical activities. These data, a subcomponent of the Princeton Data Improvement Initiative (PDII) sur-

[4] While an earlier generation of scholars criticized the DOT for its subjective, nonrepresentative, and outmoded measurement of job characteristics (Miller et al. 1980), the Department of Labor's substantial investments in the O*Net have improved this instrument relative to its predecessor (but see National Research Council 2010, 195ff.; and Handel 2013).

[5] Another key limitation is that job content measures in these databases are updated infrequently (the DOT is no longer updated), with time lags that differ among occupations. This makes it difficult to use these tools to track changes in task content within jobs.

[6] Classic works that consider the relationship between education and comparative advantage include Welch (1970) and Willis and Rosen (1979).

vey, allow us to assess the extent to which job tasks vary within (as well as between) occupations and to test whether within-occupation variation in job tasks is systematically related to workers' human capital and demographic characteristics, such as race and gender.

We further assess the value added of self-reported job tasks as predictors of labor market outcomes relative to similar occupation-level measures available from sources like the O*Net. We find that (1) *occupation-level* PDII measures have predictive power for earnings conditional on O*Net *occupation-level* measures; and (2) *person-level* PDII measures have predictive power for earnings conditional on both PDII and O*Net *occupation-level* measures.[7] This suggests that tasks are a potentially valuable tool for characterizing individual jobs in addition to broader occupations, as is the conventional practice.

In the final section of the paper, we offer two high-level empirical tests of the Roy model's implications using the PDII data, and these tests yield qualified support. Although the primary purpose of our model is to build intuition for how job tasks "should" be related to worker earnings in equilibrium, we believe that the general approach and initial empirical evidence provide a useful foundation for more comprehensive analyses.

I. How Will Job Tasks Be Rewarded in the Labor Market? Some Simple Theoretical Ideas

The Mincer (1974) earnings model provides the conceptual underpinnings for empirical analysis of the market returns to human capital investments. In the Mincer model, human capital is proxied by education and potential experience, and the coefficient on years of schooling obtained from a log earnings regression is interpreted as the compensating differential for income forgone while in school. If human capital is unidimensional and markets are competitive, the law of one price applies: the economy-wide price of human capital should be invariant across jobs. These assumptions motivate a hedonic model of earnings such as the following:

$$\ln w_i = \alpha + \beta_1 S_i + \beta_3 \text{Exp}_i + \beta_4 \text{Exp}_i^2 + \beta_3 \boldsymbol{X}_i + e_i, \tag{1}$$

where w_i is the log hourly wage of worker i, $\boldsymbol{X}_i$ is a vector of person-level covariates, S_i is years of completed schooling, and Exp_i is potential experience. In this model, $\hat{\beta}_1$ is an estimate of the market return to a year of schooling. If the primary cost of schooling is forgone earnings and capital markets function efficiently, the Mincer model further predicts that the

[7] Black and Spitz-Oener (2010) analyze the relationship between job tasks and wages in West Germany. Distinct from our approach, their task measures are constructed at the occupation rather than person level.

equilibrium rate of return to a year of education should approximately equal the market interest rate.

Does this hedonic reasoning also carry over to the interpretation of the market returns to job tasks—that is, should we expect the coefficient on job tasks in a wage regression to capture the equilibrium, economy-wide price of these tasks? Our answer to this question is no.[8] Job tasks differ from education in two key respects. First, tasks are not durable investment goods like education that must earn a well-defined market rate of return. The tasks that a worker performs on the job are an application of that worker's skill endowment to a given set of activities, and workers can modify these task inputs as job requirements change. This ongoing self-selection of workers into job tasks implies that there will not generally be a one-to-one mapping between a worker's stock of human capital and the job tasks she performs.

The second key distinction between job tasks and years of schooling is that tasks are a high-dimensional bundle of activities, the elements of which must be performed jointly to produce output. For example, flight attendants engage in both interpersonal and physical tasks, construction workers perform both analytical and physical tasks, and managers perform both analytical and interpersonal tasks. In each case, these core job tasks cannot be unbundled; each worker occupying the job must perform them.

These two observations—ongoing self-selection of workers into tasks and bundling of task demands within jobs—motivate a Roy (1951) model of the allocation of workers to job tasks. We conceive of a job, or, more broadly, an occupation, as an indivisible bundle of task demands, all of which are performed simultaneously by each worker in the occupation. We assume that workers are income maximizing. They self-select into the occupations that offer the highest wage (or, more generally, highest utility) to the bundle of tasks they are able to produce given their skill endowments. The empirical implications of this model differ significantly from the Mincerian compensating differentials framework, as we highlight below.

A. Conceptual Model

We write workers' skill endowments as a vector of task efficiencies (equivalently, abilities), where the skill endowment of worker i is written as $\Phi_i = \{\phi_{i1}, \phi_{i2} \ldots, \phi_{iK}\}$. Each element of Φ_i is a strictly positive number measuring the efficiency of worker i at task k. Thus, worker i can perform ϕ_{ik} units of task k in a given time interval. We think of Φ_i as representing a worker's stock of human capital, and her efficiency in each

[8] Our claim here is thus similar to that of Heckman and Scheinkman (1987), but our argument is an informal one.

task may be a result of human capital investments, innate abilities, or some combination. We make no further assumption on the distribution of Φ or the correlation among its elements except that Φ has continuous support on R^K_{++}.[9]

Occupations produce output using the vector of K tasks, where the productive value of tasks differs among occupation. This assumption differs from the Mincerian framework for human capital in which the marginal productivity of education is equated across sectors. It is logical for job tasks, however, due to occupation-level indivisibilities.[10]

Let the output of worker i in occupation j equal:

$$Y_{ij} = e^{\alpha_j + \Sigma_K \lambda_{jk}\phi_{ik} + \mu_i}, \tag{2}$$

where $\lambda_{jk} \geq 0 \quad \forall \quad j, k$ and μ_i is a worker-specific error term. Note that α_j is not constrained to be positive, such that a worker with insufficient skills at the occupation's key tasks would have a negative marginal product (e.g., an untrained airline pilot). We normalize the output price for each occupation at unity. This normalization is not restrictive since a logarithmic change in the market price of an occupation's output is equivalent to a multiplicative change in the exponentiated terms of (2).[11] Thus, we can summarize the production structure of occupation j with the vector $\Lambda_j = \{\alpha_j, \lambda_{j1}, \lambda_{j2}, \ldots, \lambda_{jK}\}$.

If workers are paid their marginal product, the log wage of worker i in occupation j is:

$$w_i = \alpha_j + \sum_K \lambda_{jk}\phi_{ik} + \mu_i. \tag{3}$$

Taking this production structure as given, each worker chooses the occupation j that maximizes her output and hence earnings:

$$Y_i = \max_j\{Y_{i1}, Y_{i2}, \ldots Y_{iK},\} = \max_j\{\alpha_j + \Phi_i \Lambda_j'\}. \tag{4}$$

This economy is characterized by self-selection of workers into occupations based on comparative advantage. In equilibrium, the marginal worker in occupation j is indifferent between that occupation and the

[9] The assumptions that all elements of Φ are positive and have continuous support assures that the self-selection of workers into occupations is well determined. Absent this assumption, two occupations that offered different rewards to a specific task k' but identical rewards to all other tasks could be equally attractive to a given worker (i.e., if that worker's endowment had $\phi_{k'} = 0$).

[10] Firpo et al. (2011) adopt a similar assumption.

[11] We could equivalently write eq. (2) as $Y_{ij} = \exp\left[\pi_j\left(\alpha_j' + \Sigma_K \lambda_{jk}'\phi_{ik} + (\mu_i/\pi_j)\right)\right]$, where $\pi_j > 0$ is a productivity shifter that reflects market demand and other factors, $\alpha_j' = \alpha_j/\pi_j$, and $\lambda_{jk}' = \lambda_{jk}/\pi_j$.

next best alternative.[12] Inframarginal workers, however, strictly prefer the occupation they have selected relative to any alternative. Observe that task returns in this model are occupation specific: $\partial w/\partial \phi_k|_{J=j} = \lambda_{jk}$. The equilibrium of the model ensures that workers are employed in the occupation that has the highest reward to their bundle of tasks. But this does not imply that workers necessarily receive the maximum market reward to each element in their task bundle or that each element is equally valuable in all occupations.

B. Some Straightforward Empirical Implications

As is well understood, identifying the market locus of the "return to skills" in the presence of self-selection is not empirically straightforward (Heckman and Scheinkman 1986; Heckman and Honoré 1990). Given the nonrandom assignment of workers to occupations, a regression of log wages on workers' job tasks will not generally recover the average returns to those tasks. Concretely, workers with high efficiencies in given tasks will sort toward occupations that have high rewards for those tasks. The average "return to tasks" observed in the data will therefore not correspond to the average return over all occupations (e.g., if workers were randomly assigned to occupations).

Estimating task returns using observational data is particularly challenging when the rewards to clusters of tasks are correlated. Consider, for example, a hypothetical case where the marginal productivity of physically demanding (manual) tasks is strictly positive in all occupations ($\lambda_{jm} > 0 \;\; \forall \;\; j$) but the productivity of manual tasks is highest in occupations that have comparatively low returns to other major task categories (e.g., analytical tasks), so $\mathrm{Cov}(\lambda_{jm}, \lambda_{ja}) < 0$. Let M_i and A_i denote the intensity of worker i's manual and analytical task input on the job, respectively. An ordinary least squares (OLS) regression of log wages on individual task input of the following form,

$$w_i = \alpha + \beta_A A_i + \beta_M M_i + e_i, \tag{5}$$

may potentially recover a "return" to physically demanding tasks that is negative (i.e., $\hat{\beta}_M < 0$). This spurious inference would arise because the cross-occupation correlation between the returns to physical and analytical

[12] This assumes that occupations are sufficiently "close together" that there is a marginal worker in each occupation. With a finite set of occupations, it is conceivable that all workers would strictly prefer the occupation they are in. This would not affect our substantive conclusions.

tasks is negative, even though the within-occupation return to physical tasks is uniformly positive.[13]

Without further strong assumptions on the distribution of task endowments, it would be infeasible to identify the structural parameters that underlie this model. The model does, however, imply some testable restrictions on the relationship between tasks and wages that do not rely on these parameters.

PROPOSITION 1. Let Γ be the set of all occupations that have nonzero employment in equilibrium. For each occupation $j \in \Gamma$, it must be the case that Λ_j is not vector dominated by some other occupation $\Lambda_{j'}$ where $j' \in \Gamma$.

This proposition says that for occupation j to attract workers (and thus belong to Γ), there cannot be an alternative occupation j' that has both a higher intercept and a higher return to all tasks. If such an occupation existed, all workers in occupation j would strictly prefer occupation j' and hence $j \notin \Gamma$.

PROPOSITION 2. For all occupations $j \in \Gamma$, the cross-occupation covariance among task returns cannot be uniformly positive across all task pairs k, k'. That is, either $\mathrm{Cov}(\lambda_k, \lambda_{k'}) \leq 0$ for some k, k', or $\mathrm{Cov}(\alpha, \lambda_k)$ for some k, or both.

To see why this proposition holds, consider a case where all occupations use only one task k, so each occupation j can be described by the double $\Lambda_j = \{\alpha_j, \lambda_j\}$. For each occupation $j \in \Gamma$, it must be the case that $Y_j(\phi_k) > Y_{j'}(\phi_k)\ \forall j \neq j \cap j' \in \Gamma$ for some value of ϕ_k. That is, there must be a worker i who prefers occupation j to j'. Given that $j' \in \Gamma$, however, there must also be some value of $\phi_{k'} \neq \phi_k$ such that $Y_j(\phi_{k'}) < Y_{j'}(\phi_{k'})$, so some worker i' prefers j' to j. Jointly, these restrictions imply that

$$(\alpha_j - \alpha_j') \times (\lambda_j - \lambda_j'). \tag{6}$$

That is, the returns to tasks must negatively covary within the set of occupations that have positive employment. Were this not so, some subset of workers could be made strictly better off by changing occupations. This reasoning extends to the case of multiple tasks: the covariances among task returns, and between task returns and the intercept, cannot be uni-

[13] This bias will be present if there is nonzero cross-occupation correlation between the returns to physical and analytical tasks. The sign and magnitude of the bias will depend on both the sign and magnitude of the covariance term and the magnitude of cross-occupation variances in task returns.

formly positive.[14] We explore this proposition below, but it should be acknowledged that it does not offer a very restrictive test of the Roy model. It establishes a necessary but not sufficient condition for the data to be consistent with self-selection, which is that occupations with positive employment are preferred by some, but not all, workers depending upon their task endowments.

In the subsequent data analysis, we also analyze a second empirical implication of the Roy model: workers who have higher efficiency—equivalently, ability—in a given task domain will generally self-select into occupations that have a higher return to that task. To formalize this idea, and delineate under what conditions it holds, we extend the simple case considered above in proposition 2 to a parametric selection setting with normally distributed task efficiencies.

Consider a case with two occupations, j and j', and two distinct tasks, k and k'. Let the corresponding price vectors be $\Lambda_j = \{a_j, \lambda_1, \lambda_2\}$ and $\Lambda_{j'} = \{\alpha_j', \lambda_1', \lambda_2'\}$. Log wages continue to be given by equation (3). To simplify the analysis, we assume that occupation j rewards only task 1 and occupation j' rewards only task 2: $\lambda_1, \lambda_2' > 0$ and $\lambda_2 = \lambda_1' = 0$. Let the population distribution of worker endowments of tasks 1 and 2 be given by the bivariate unit normal distribution:

$$\begin{bmatrix} \varepsilon_1 \\ \varepsilon_2 \end{bmatrix} \sim N\left(\begin{bmatrix} 0 \\ 0 \end{bmatrix}, \begin{bmatrix} 1 & . \\ \sigma_{12} & 1 \end{bmatrix} \right). \tag{7}$$

To conserve notation, define $v = \varepsilon_1 - \varepsilon_2$ equal to the difference in a worker's efficiency in task 1 versus task 2—so, a worker with $v > 0$ has relatively greater efficiency in task 1 while a worker with $v < 0$ has relatively greater efficiency in task 2.

Following the derivation in Borjas (1994), we can calculate the expected task endowments of workers who self-select into each occupation as:

$$\begin{aligned} E[\varepsilon_1 | i = j] &= \frac{\lambda_1 \lambda_2'}{\sigma_v} \left(\frac{\lambda_1}{\lambda_2'} - \rho \right) \left(\frac{\phi(-z)}{\Phi(z)} \right) \\ E[\varepsilon_2 | i = j'] &= \frac{\lambda_1 \lambda_2'}{\sigma_v} \left(\rho - \frac{\lambda_2'}{\lambda_1} \right) \left(\frac{\phi(-z)}{\Phi(z)} \right), \end{aligned} \tag{8}$$

where $z = (\alpha_j' - \alpha_j)/\sigma_v$, $\rho = \lambda_1 \lambda_2' \sigma_{12} / \lambda_1 \lambda_2' \sigma_1 \sigma_2 = \sigma_{12}$, and $\phi(z)/\Phi(-z)$ is the Inverse Mills Ratio.

These equations imply that workers with above average capabilities in tasks 1 and 2, respectively, will self-select into the occupations that differentially reward these tasks (j and j') if and only if the population correlation between workers' abilities in these two tasks is not too high.

[14] It does not need to be negative for all elements, however.

Proposition 3. A necessary condition for workers to be positively self-selected on task 1 capability into occupation j and on task 2 capability into occupation j' is that

$$\rho < \min\left(\frac{\lambda_1}{\lambda_2'}, \frac{\lambda_2'}{\lambda_1}\right). \tag{9}$$

A sufficient condition for this expression to hold is that $\rho \leq 0$: worker abilities in tasks 1 and 2 are either uncorrelated or negatively correlated.

This proposition says that if the correlation between worker abilities in each task is not too high, workers will self-select into occupations that offer high returns to the tasks in which they are particularly well endowed—meaning that self-selection takes the form of comparative advantage.

What are the empirical implications of proposition 3 for wages? If we were to estimate equation (5) above by OLS with two tasks, the presence of heterogeneous task returns implies that this equation would be too restrictive: the β's should be allowed to vary by occupation. We can make progress, however, by observing that self-selection implies that we will observe nonzero covariances between occupation-level task returns and the task endowments of workers who self-select into these occupations. To recover these covariances, we can estimate an augmented version of equation (5) where we interact occupational task means with worker-level task inputs:

$$w_{ij} = \alpha + \beta_A A_i + \beta_M M_i + \delta_A \overline{A}_j + \delta_M \overline{M}_j + \gamma_A A_i \times \overline{A}_j + \gamma_M M_i \times \overline{M}_j + e_{ij}. \tag{10}$$

Following proposition 3, two cases emerge that make different predictions on the signs of the interaction terms γ_A, γ_M in this equation.

The first case, which we refer to as *comparative advantage*, is a setting where workers are positively self-selected into *each* occupation. This occurs when the correlation between worker abilities across tasks is sufficiently low that equation (9) is satisfied. This implies that there will be a positive covariance between occupational task returns and the task endowments of workers in each occupation. Hence, task returns will be higher in occupations that differentially use each task. Formally, this implies that γ_A, $\gamma_M > 0$.

Conversely, if the population distribution of skills has a strong element of *absolute advantage*—that is, workers who excel at task 1 also excel at task 2—then positive self-selection on task 1 into occupation j must imply negative self-selection on task 2 into occupation j', and vice versa. Hence, if one occupation has workers who are particularly productive at the task that the occupation differentially rewards, the second occupation will have workers who are relatively unproductive at the task that the occupation differentially rewards.[15] The empirical prediction here is therefore weaker: at least one of the task interaction terms must be positive. Formally, $\min[\gamma_A,\ \gamma_M] > 0$.

In the subsequent empirical sections, we test the two sets of complementary empirical implications following from propositions 2 and 3: task returns across occupations are not uniformly positively correlated (i.e., they are negatively correlated for at least one task category); and workers are positively self-selected into occupations along at least one task dimension. Since these implications are admittedly not highly restrictive, we view the tests of the model as exploratory rather than dispositive.

Although the implications that we develop here are cross-sectional, a theoretical setting in which workers differ in their productivity across tasks and task returns differ across occupations also has immediate implications for the evolution of job changes and wage growth over the course of the career. Lazear (2009) provides a general theoretical statement of this problem, while Neal (1999), Gibbons et al. (2005), and Gathmann and Schönberg (2010) develop and test detailed empirical implications. Gathman and Schönberg's (2010) longitudinal study, which employs occupation-level measures of job tasks, is particularly germane. A key result is that when workers change jobs, they move mostly to new occupations that have task requirements that are similar to those of their previous occupations. Although we cannot explore similar longitudinal patterns in the cross-sectional data collected for this analysis, we view this body of work linking workers' task productivities to their employment and wage dynamics as extremely promising.

II. Data Sources

The primary data source for our analysis is a module of the Princeton Data Improvement Initiative survey (PDII) that collects data on the cognitive, interpersonal, and physical job tasks that workers regularly perform on their jobs. Our primary analyses focus on three broad dimensions motivated by the conceptual framework in Autor et al. 2003: abstract problem solving and creative, organizational, and managerial tasks ("Abstract tasks"); routine, codifiable cognitive and manual tasks that

[15] Note that absolute advantage is a special case of comparative advantage where there is a positive hierarchical ranking of workers by ability across all activities. Even in this case, the assignment of workers to occupations is determined by comparative advantage: labor market clearing implies that all skill groups will hold comparative advantage (after accounting for labor costs) in some set of occupations. What is distinctive about the absolute advantage case relative to the standard comparative advantage case is that in equilibrium not all workers are assigned to the activity in which they have the highest productivity.

follow explicit procedures ("Routine tasks"); and nonroutine manual job tasks that require physical adaptability ("Manual tasks").

Four items from the PDII elicit information on Abstract job demands: (1) the length of longest document typically read as part of the job (ranging from one page or less to more than 25 pages); (2) frequency of mathematics tasks involving high school or higher mathematics (algebra, geometry, trigonometry, probability/statistics, or calculus); (3) frequency of problem-solving tasks requiring at least 30 minutes to find a good solution; and (4) proportion of workday managing or supervising other workers. The items are combined into a standardized scale of Abstract tasks using the first component of a principal components analysis, which accounts for 41% of their variation.

Four items from the PDII were used to identify jobs with Routine tasks: (1) proportion of the workday spent performing short, repetitive tasks and complete absence of face-to-face interactions with (2) customers or clients, (3) suppliers or contractors, or (4) students or trainees.[16] The items are combined into a standardized scale of Routine tasks using the first component of a principal components analysis, which accounts for 56% of their variation.

A single PDII item elicits information on Manual job tasks: proportion of the workday spent performing physical tasks such as standing, operating machinery or vehicles, or making or fixing things by hand. This variable is also standardized for our analyses.

For most analyses, we use a consistent sample of cases with full information on tasks, demographics, human capital, and wages, and with at least two cases per six-digit Standard Occupational Classification (SOC) system ($n = 1{,}333$). For analyses that estimate returns to tasks separately by occupation, the regression model requires at least five cases per occupation for identification, which further limits the sample.[17] Summary statistics for our primary sample are given in appendix table A1.

Many of the task questions contained in the PDII are adapted from the survey of Skills, Technology, and Management Practices (STAMP) written and fielded by Handel (2007, 2008a, 2008b; see also Hilton 2008). Handel (2008a) provides an extensive discussion of the conceptual basis,

[16] These questions are from the PDII module that measures the suitability of jobs for international offshoring (Blinder and Krueger 2008).

[17] Our precise sample restrictions in sequence, based on an initial PDII sample of 2,500 cases, are: currently working (238 observations dropped); ages 18–64 (211 observations dropped); nonmissing task measures (35 observations dropped); nonmissing education (6 observations dropped); nonmissing wage data (486 observations dropped); nonmissing, nonmilitary, and nonfarm occupation (36 observations dropped); at least two valid observations in each occupation (168 observations dropped). Finally, in the exercise where five valid observations are required per occupation, an additional 405 observations are dropped.

validity, and reliability of the STAMP measures, which generalizes to the closely related PDII measures. Handel (2008b) presents preliminary results from the STAMP survey, which can be compared to results presented below.

An alternative source of information on job content is the US Department of Labor's Occupational Information Network (O*Net), which contains occupation-level measures and replaces the *Dictionary of Occupational Titles* as an official career counseling tool. The O*Net database, many years in the making, is only beginning to be used by academic researchers but is a useful point of comparison. If parallel measures from the PDII and O*Net are highly correlated, this offers evidence of what psychologists call convergent validity. Comparing results across wage regressions provides evidence on the relative strengths of two different approaches to measuring task input (Handel 2008a) and the value added of person-level relative to occupation-level job content measures. The O*Net-based Abstract, Routine, and Manual scales are from Acemoglu and Autor (2011) and use O*Net items that appear likely to capture similar dimensions of task input as the PDII. The O*Net scales are matched to the PDII person records at the six-digit SOC 2000 occupation level. The appendix provides further details on the O*Net measures.

Other approaches to providing job task measures alongside human capital variables at the person level include the German IAB/BIBB data set and the British Skills Survey, which are repeated cross-sections of workers over one or two decades (Spitz-Oener 2006; Felstead et al. 2007; Dustmann et al. 2009). If the PDII analyses prove illuminating, they may suggest the utility of a similar time series for the United States.

III. Job Tasks: Levels and Differences among Education and Occupation Groups

A. Descriptive Statistics

The PDII measures provide a snapshot of the skill levels and task content of US jobs (table 1). Only about one-quarter (24%) of wage and salary workers use any kind of higher-level math on at least a weekly basis, while about one-third (37%) read documents longer than six pages on a regular basis as part of their jobs. Along with similar results from the STAMP survey, these are the first figures on the actual levels of math and reading that individuals use on their jobs. A far larger percentage report engaging in extended problem solving either daily (47%) or weekly (29%). Approximately 29% manage or supervise others at least half the time on their jobs.

More than half (51%) of wage and salary workers have a lot of contact with customers or clients as part of their jobs. Not surprisingly, far fewer people have a lot of contact with students or trainees (22%) and suppliers (11%) as part of their jobs.

Slightly more than half (51%) of workers report spending more than half their time on short, repetitive tasks, and almost two-thirds (60%) report spending at least half their time doing physical tasks, such as standing, handling objects, or operating equipment.

Because these characteristics describe important dimensions of both jobs and the persons selected into them, one expects the measures to be associated with both demographic and job characteristics. Subsequent columns of table 1 summarize PDII responses by gender, race (white, black, Hispanic), and education (less than high school, high school only, some college, college degree or greater).[18] There are striking differences across gender, race, and education categories in all task activities. For example, females are substantially more likely than males to spend at least half of their time on repetitive tasks (58% versus 44%), and blacks and Hispanics are substantially more likely than whites to spend at least half of their time on physical job tasks (these percentages are 56%, 70%, and 76% for whites, blacks, and Hispanics, respectively).

The lower panel of table 1 presents means and standard deviations for the standardized task scales. Most notably, the gap between high school dropouts and those with college or more is about one standard deviation for Abstract and Manual tasks and about three-quarters of a standard deviation for Routine.

Table 2 shows breakdowns by one-digit occupation. In this case, the largest and smallest means differ by approximately 1.4 standard deviations for Manual tasks, by 1.3 standard deviations for Abstract tasks, and by 1.2 standard deviations for Routine tasks. Broad occupation does a better job than personal education in identifying individuals who perform most of the interpersonal tasks.

The first two panels of table 3 present correlations of the items and scales with one another and with education and six-digit occupation. Education correlates moderately to strongly with the scales for Manual tasks (−0.41), Routine tasks (−0.39), and Abstract tasks (0.38), as well as the item for reading (0.33). The correlations with detailed occupation were calculated by regressing item and scale values on the 241 unique six-digit occupation dummies present in the data, and taking the square root of R-squared to calculate the multiple correlation coefficient. These correlations are much larger than those involving personal education, ranging from 0.60 to 0.79. This is not entirely surprising given that the occupation level regressions contain 241 explanatory variables whereas the bivariate

[18] A fourth race group, Asian, makes up 1.5% of the sample. Because of the very small number of respondents (12), we do not separately tabulate this group.

Table 1
PDII Task Measures by Major Demographic Group: Employed Workers Ages 18–64

	All	Male	Female	White	Black	Hispanic	< HS Grad	HS Grad	Some Coll	Coll+
Time on physical tasks:										
Almost all	46.7	48.4	44.8	42.0	51.0	67.7	76.4	63.8	48.5	21.8
Half or more	13.7	15.7	11.5	14.3	19.3	8.7	5.2	16.9	16.1	11.3
Less than half	39.6	35.9	43.7	43.7	29.7	23.7	18.4	19.3	35.4	66.8
Time on repetitive tasks:										
Almost all	33.0	27.4	39.4	29.1	36.4	50.1	54.9	49.5	32.9	12.2
Half or more	16.5	15.1	18.1	16.8	10.7	17.4	14.3	15.0	23.9	13.0
Less than half	50.5	57.6	42.6	54.1	52.8	32.5	30.8	35.5	43.3	74.9
Time on managing/supervising:										
Almost all	19.8	22.2	17.2	20.6	24.0	15.5	26.7	13.6	20.2	23.4
Half or more	9.4	10.4	8.3	10.0	4.5	10.4	4.5	4.4	8.6	15.8
Less than half	70.8	67.4	74.6	69.4	71.5	74.1	68.7	81.9	71.2	60.8
Solve problems of 30+ minutes:										
Daily	42.9	46.2	39.1	44.9	31.7	40.5	30.5	27.3	44.3	59.4
Weekly	28.7	30.0	27.3	29.7	27.0	26.2	15.4	36.1	27.5	26.6
Less than weekly	28.4	23.8	33.6	25.4	41.2	33.3	54.2	36.6	28.2	14.1
Use high school+ math:										
Daily	16.1	17.6	14.4	14.9	15.2	21.3	16.0	15.3	15.0	17.8
Weekly	8.3	11.0	5.3	9.4	5.2	6.4	2.7	6.8	8.3	11.2
Less than weekly	75.6	71.4	80.2	75.8	79.6	72.3	81.3	77.9	76.7	71.1

Longest document typically read at job:										
6−25+ pages	37.4	37.9	36.9	40.9	29.1	24.8	21.1	20.7	32.1	61.1
2–5 pages	28.4	27.4	29.4	29.3	31.4	24.3	12.9	25.6	37.5	28.2
1 or fewer	34.2	34.7	33.7	29.9	39.5	50.9	66.0	53.7	30.4	10.7
Have a lot of face to face contact with (excluding coworkers):										
None	11.9	10.5	13.5	10.9	15.2	15.2	11.6	16.1	11.2	8.6
Customers/clients	50.9	46.2	56.2	51.3	68.3	41.6	36.3	53.2	56.2	48.8
Suppliers/contractors	11.2	16.1	5.7	10.8	17.9	10.7	6.3	14.8	11.7	9.0
Students/trainees	22.2	18.3	26.6	20.8	34.3	19.9	13.0	23.5	18.1	26.5
Patients	11.3	5.8	17.4	11.3	17.4	7.5	5.3	6.3	17.6	12.8
Means and standard deviations of PDII composite measures:										
1. Abstract	.00	.13	−.15	.07	−.17	−.18	−.49	−.38	−.03	.49
	(1.00)	(.99)	(.99)	(1.01)	(.98)	(.92)	(.85)	(.90)	(.98)	(.92)
2. Routine	.00	−.11	.13	−.07	.05	.31	.31	.32	.06	−.42
	(1.00)	(.92)	(1.07)	(.98)	(1.03)	(1.04)	(.97)	(.94)	(.99)	(.92)
3. Manual	.00	.05	−.06	−.10	.20	.39	.55	.42	.10	−.60
	(1.00)	(.99)	(1.01)	(1.01)	(.88)	(.87)	(.75)	(.80)	(.95)	(.96)
Sample share	100.0	53.1	46.9	72.6	9.6	15.8	9.3	31.1	25.3	34.2

NOTE.—n = 1,333. See text for details of sample construction; white and black demographic categories exclude Hispanics. HS = high school; Coll = college.

Table 2
PDII Task Measures by Occupation: Employed Workers Ages 18–64

	Manager	Professional Specialist	Technical/Sales	Clerical	Construction/ Repair	Production	Transport	Service Occupations
Time on physical tasks:								
Almost all	17.7	19.7	44.4	32.7	73.5	75.5	79.6	79.4
Half or more	7.2	17.8	23.0	10.5	17.1	16.9	17.9	4.7
Less than half	75.1	62.4	32.6	56.8	9.4	7.6	2.5	15.8
Time on repetitive tasks:								
Almost all	4.6	11.4	39.0	43.2	18.6	50.8	65.1	53.4
Half or more	10.9	12.7	17.3	21.2	26.5	17.4	17.0	16.0
Less than half	84.6	75.9	43.7	35.6	55.0	31.9	17.9	30.5
Time on managing/supervising:								
Almost all	49.8	15.7	20.0	11.6	19.4	17.9	12.5	17.0
Half or more	16.8	12.2	12.3	3.5	11.3	10.1	2.9	5.6
Less than half	33.5	72.0	67.8	84.9	69.4	72.0	84.6	77.4
Solve problems of 30+ minutes:								
Daily	72.0	58.9	32.5	35.2	52.4	33.6	15.9	27.3
Weekly	18.9	28.3	32.8	31.6	33.9	39.1	39.5	20.6
Less than weekly	9.1	12.8	34.7	33.1	13.7	27.2	44.6	52.1
Use high school+ math:								
Daily	17.0	19.7	16.2	14.7	24.0	21.9	25.7	3.2
Weekly	18.5	8.3	6.2	3.4	18.7	11.7	2.4	4.6
Less than weekly	64.5	72.0	77.5	82.0	57.3	66.4	71.9	92.2

Longest document typically read at job:								
6−25+ pages	58.0	58.8	29.9	27.4	34.8	13.5	16.6	27.2
2–5 pages	29.6	32.6	34.5	28.7	32.8	28.2	15.0	21.5
1 or fewer	12.4	8.6	35.7	43.9	32.4	58.3	68.4	51.3
Have a lot of face to face contact with (excluding coworkers):								
None	4.3	10.2	2.8	29.3	4.8	22.4	17.5	8.1
Customers/clients	39.5	51.2	83.3	37.0	42.5	28.5	49.7	58.2
Suppliers/contractors	18.1	5.8	14.4	7.6	24.1	4.5	24.8	6.2
Students/trainees	15.8	36.1	27.1	14.0	18.6	9.2	6.6	23.3
Patients	2.8	18.9	8.1	9.7	0.5	3.5	1.6	20.7
Means and standard deviations of PDII composite measures:								
1. Abstract	.80	.44	−.12	−.34	.34	−.21	−.52	−.57
	(.78)	(.86)	(.96)	(.88)	(.81)	(.96)	(.97)	(.88)
2. Routine	−.65	−.41	−.06	.57	−.22	.52	.58	.21
	(.70)	(.91)	(.73)	(1.18)	(.72)	(1.14)	(.85)	(.86)
3. Manual	−.77	−.54	.10	−.31	.62	.65	.76	.60
	(.91)	(.93)	(.91)	(.99)	(.62)	(.61)	(.37)	(.71)
Sample share	11.3	23.5	12.1	14.6	7.2	5.7	7.5	18.1

NOTE.—n = 1,333. See text for details of sample construction.

Table 3
Correlations among PDII Task Variables and among PDII and O*Net Task Variables

	A. PDII Survey Measures									
	1	2	3	4	5	6	7	8	9	10
1. Manage	1.00									
2. Problem solving	.22	1.00								
3. Math	.14	.24	1.00							
4. Read	.12	.21	.17	1.00						
5. Routine	−.13	−.25	−.06	−.21	1.00					
6. Physical	−.10	−.27	−.03	−.29	.40	1.00				
7. Customer	.09	−.02	−.09	−.02	.05	.17	1.00			
8. Suppliers	.09	.11	.11	−.01	.00	.05	.19	1.00		
9. Training	.14	.04	−.01	.06	−.07	.06	.19	.07	1.00	
10. Education	.14	.29	.11	.33	−.39	−.41	.03	−.04	.10	1.00
11. Occupation-level R-value	.68	.65	.62	.64	.70	.79	.70	.60	.66	.78

	B. Correlations among Composites of PDII Survey Measures				C. Correlations between PDII and O*NET Task Measures	
	(1)	(2)	(3)	(4)	Worker Level (1)	Mean (2)
1. Abstract	1.00				.47	.65
2. Routine	−.32	1.00			.33	.48
3. Manual	−.31	.22	1.00		.50	.63
4. Education	.38	−.33	−.41	1.00		
5. Occupation-level R-value	.73	.69	.79	.78		

Note.—n = 1,333 except in final column of panel C, where n = 241 occupations. Statistics in bottom row of panels A and B are the R-values (square root of R-squared) from regressions of the PDII task measures on three-digit occupation dummies. Panel C employs the Abstract, Routine, and Manual measures constructed using the O*Net database and described in the appendix. The first column of panel C reports the correlation between the person-level PDII measure and the corresponding O*Net occupation-level mean measure, while the second column reports the correlation between the occupation-level mean PDII measure and the corresponding O*Net measure.

correlations contain, by definition, only one explanatory variable. Taken together, the PDII task measures show generally sensible patterns of variation across education and occupational groups and provide concrete information on what people do on their jobs and the share of the workforce performing each task at different intensities.

The third panel of table 3 presents correlations between the O*Net scales and the corresponding PDII scales, measured both at the individual level (col. 1) and averaged by detailed occupation to match the level of O*Net's aggregation (col. 2). The occupation-level correlations in column 2 are larger, which is expected given that the O*Net measures only vary at the occupation level and thus cannot covary with PDII responses within occupations.

The PDII measures of Abstract and Manual tasks correlate strongly with their O*Net counterparts, particularly when PDII occupation means are used (0.63–0.65). The correlations between the PDII and O*Net Routine scales are somewhat lower, but still moderate to strong at 0.33 and 0.48. These results are evidence of a reasonably high degree of convergent validity for the PDII measures.

B. Explaining Differences in Job Tasks: The Roles of Human Capital, Occupation, and Demographic Characteristics

Although almost all analyses of job tasks treat tasks as an occupation-level construct, a virtue of the PDII's individual-level task measures is that they permit investigation of the variance of job tasks within occupations and the degree to which this variation is systematically related to worker as well as job attributes. This section analyzes the extent to which the tasks workers perform on the job can be explained by their individual human capital, demographic attributes, and the technical requirements of the job itself, proxied by detailed occupation dummies. Our descriptive OLS regressions take the following form:

$$T_{ij} = \alpha + \delta_1 S_i + \delta_1 X_i + \gamma_j + e_{ij}, \tag{11}$$

where the vector S includes human capital measures (education, potential experience, primary language), X is a vector of demographic characteristics (race, ethnicity, sex), and γ is a vector of 240 occupation dummies (with one omitted).[19] The reference group for this regression is white male English-speaking high school graduates.[20]

Table 4 presents regressions results for the standardized Abstract, Routine, and Manual scales. Models 1, 3, and 5 use demographic and human

[19] For primary language a dummy variable equals one for individuals who required the Spanish-language version of the PDII questionnaire.

[20] We code the 4.7% of respondents in our main sample who were interviewed in Spanish as primary Spanish-language speakers.

Table 4
Regressions of Standardized PDII Task Variables on Demographics, Human Capital Measures, and Occupation Dummies

	Dependent Variable					
	Abstract		Routine		Manual	
	(1)	(2)	(3)	(4)	(5)	(6)
Less than high school	.05	.01	−.21	−.06	.00	.04
	(.10)	(.11)	.10	(.11)	(.10)	(.09)
Some college	.34	.04	−.26	−.17	−.27	.07
	(.07)	(.07)	.07	(.07)	(.06)	(.06)
College	.71	.10	−.56	−.20	−.87	−.29
	(.07)	(.08)	.07	(.09)	(.07)	(.07)
Postcollege	.99	.33	−.91	−.33	−1.09	−.45
	(.08)	(.10)	.09	(.11)	(.08)	(.09)
Experience	.03	.02	−.03	−.02	−.02	−.01
	(.01)	(.01)	(.01)	(.01)	(.01)	(.01)
Experience^2/100	−.08	−.05	.05	.04	.03	.02
	(.02)	(.02)	(.02)	(.02)	(.02)	(.01)
Spanish language	−.65	−.61	.54	.54	.31	.23
	(.14)	(.14)	(.15)	(.15)	(.14)	(.12)
Female	−.31	−.04	.27	.15	−.06	.07
	(.05)	(.06)	(.05)	(.06)	(.05)	(.05)
Black	−.13	.05	−.01	.00	.12	.05
	(.08)	(.08)	(.08)	(.09)	(.08)	(.07)
Hispanic	.09	.35	.12	.02	.17	.00
	(.08)	(.08)	(.08)	(.09)	(.07)	(.07)
Asian	−.12	−.28	.03	.21	−.17	.04
	(.17)	(.17)	(.17)	(.18)	(.16)	(.15)
240 occupation dummies	No	Yes	No	Yes	No	Yes
R-squared	.21	.55	.16	.49	.25	.65
F(Education variables)	47.6	2.7	33.7	2.7	69.9	11.6
p-value	.00	.03	.00	.03	.00	.00
F(Gender + race)	11.6	5.4	7.5	1.6	2.5	.6
p-value	.00	.00	.00	.16	.04	.67

NOTE.—n = 1,333. Standard errors are in parentheses. All models include a constant and are weighted by sampling weights.

capital variables to predict the task content of jobs. These models explain 16%–25% of the variation in the task measures. Augmenting these models with 240 detailed occupation dummies in columns 2, 4, and 6 increases the explanatory power to between 49% and 65%. All of the effects of education on Abstract tasks except for postcollege are fully mediated by occupational assignment—that is, conditioning on occupation dummies substantially attenuates the coefficients and eliminates their statistical significance. The relationships between education and performance of Routine and Manual tasks tend to remain significant after the addition of occupation dummies, but the coefficients drop substantially. By contrast, the inclusion of occupation controls has little effect on the strong negative association between Spanish-language primacy and Abstract tasks on the one hand, and the strong positive associations between Spanish-language primacy and use of Routine and Manual tasks on the other hand. Females' lower use of Abstract tasks, controlling for human capital, is fully mediated by occupation, while their higher use of Routine tasks persists after controlling for occupation. None of the coefficients for black are significant, while Hispanic ethnicity seems to be positively related to Abstract tasks once occupation is controlled.

In sum, the models suggest that a substantial proportion of Abstract task content is "hard wired" into occupations. Individual human capital remains relevant, however, for workers with a graduate education and for Spanish-language speakers, even after accounting for occupation effects. While the substantial female-male gap in the use of Abstract tasks is entirely accounted for by occupation, the higher propensity of females to engage in Routine tasks is not.[21]

These results and others not reported (2009) are notable for revealing the structuring power of occupations as determinants of job content. Indeed, occupation is the dominant measurable predictor of job tasks in our data. Alongside this fact, measures of human capital—in particular, higher education and Spanish-language primacy—are significant predictors of within- as well as between-occupation variation in job tasks. Human capital therefore plays a dual role in determining workers' job tasks, both allocating workers to occupations and influencing their job tasks within occupations (although it is apparent that the occupation channel is quantitatively larger). Race and sex are also strong predictors of workers' job tasks across all categories. But the relationship between race, sex, and job tasks runs largely, although not entirely, through occupational assignment; we find relatively few systematic race or sex differences in job task demands among workers within occupations.

IV. Job Tasks and Wages: Descriptive Regressions

A. Predicting Wages Using the PDII Measures

Industrial psychologists typically view occupational titles as coherent, well-defined job categories rather than merely as pragmatic classification tools, and hence tend to treat all within-occupation variation as measurement error (Harvey 1991; Peterson et al. 1999). To what extent does within-occupation variation in self-reported job tasks capture substantive differences, rather than noise, in job content? If self-reported variation in job tasks is a robust predictor of wages, this would provide prima facie

[21] Bertrand, Goldin, and Katz (2009) find that among US workers obtaining an MBA from a top US business school between 1990 and 2006, substantial gender gaps in career advancement develop and accumulate within a few years of graduation, reflecting differences in training prior to MBA completion, differences in career interruptions, and differences in weekly hours.

Table 5
OLS Regressions of Log Hourly Wages on Task Scales, Demographic Variables, and Occupation Dummies

	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Abstract		.20		.12		.07	.07
		(.02)		(.02)		(.02)	(.02)
Routine		−.10		−.03		−.03	−.01
		(.02)		(.01)		(.02)	(.02)
Manual		−.19		−.11		−.15	−.11
		(.02)		(.02)		(.02)	(.02)
Less than high school	.10			.09	.07		.08
	(.06)			(.06)	(.06)		(.06)
Some college	.17			.09	.06		.06
	(.04)			(.04)	(.04)		(.04)
College	.53			.34	.25		.21
	(.04)			(.04)	(.05)		(.05)
Postcollege	.75			.49	.41		.33
	(.05)			(.05)	(.06)		(.06)
Experience	.04			.03	.02		.02
	(.00)			(.00)	(.00)		(.00)
Experience^2/100	−.06			−.05	−.03		−.03
	(.01)			(.01)	(.01)		(.01)
Spanish language	−.55			−.42	−.34		−.27
	(.08)			(.08)	(.08)		(.08)
Female	−.30			−.26	−.12		−.11
	(.03)			(.03)	(.04)		(.03)
Black	−.13			−.10	−.13		−.12
	(.05)			(.04)	(.05)		(.05)
Hispanic	−.08			−.07	−.01		−.03
	(.04)			(.04)	(.05)		(.05)
Asian	.13			.13	.09		.11
	(.10)			(.09)	(.10)		(.10)
240 occupation dummies	No	No	Yes	No	Yes	Yes	Yes
R-squared	.39	.30	.61	.45	.65	.64	.67
F(Education + demographic variables)	59.8			26.2	10.4		7.7
p-value	.00			.00	.00		.00
F(Task measures)		192.1		47.9		27.3	16.0
p-value		.00		.00		.00	.00
F(Occupation dummies)			7.1		3.3	4.1	2.8
p-value			.00		.00	.00	.00

NOTE.—n = 1,333. Standard errors are in parentheses. All models include a constant and are weighted by sampling weights.

evidence that self-reported task variation is likely to be informative about job content even within occupations.[22]

We examine the relationship between tasks and wages in table 5 by regressing workers' log hourly wages on their self-reported job tasks, as well as human capital, demographic background, and detailed occupation vari-

[22] An alternative interpretation would be that omitted worker characteristics affect both wages and self-reported jobs tasks but do not affect actual job tasks

ables. As a benchmark, column 1 presents a standard cross-sectional Mincerian wage regression of hourly wages on human capital and demographic measures. All variables in this regression have the expected signs and magnitudes. The R-squared of this model is equal to 0.39, comparable to standard cross-sectional models estimated using the Current Population Survey.

Column 2 replaces the human capital and demographic controls with the three tasks scales, which predict substantial wage differentials. A one standard deviation increase in the Abstract task scale is associated with a 20% wage premium, while similar increases in Routine and Manual tasks are associated with wage penalties of 10% and 19%, respectively. By themselves, the three task scales account for 30% of the variation in log wages, which is 25% less than the full set of human capital and demographic measures. When 240 detailed occupation dummies are used in place of the task measures (col. 3), they account for 61% of wage variation.

The remainder of the table demonstrates that these three sets of variables—human capital and demographics, job tasks, and occupation—capture distinct sources of wage variance. The task measures remain significant predictors of wages conditional on either human capital and demographic measures (col. 4) or a full set of occupation dummies (col. 6). Similarly, the human capital measures are also robust to inclusion of either task measures (col. 4) or occupation variables (col. 5). Indeed, when all three clusters of variables are entered simultaneously, each is a significant predictor of wages (col. 7). Notably, comparing the Wald tests for the joint significance of each group of variables (bottom row of table 7), we find that the F-statistic for the task measures is substantially larger than for the other two groups of variables.

While statistical significance is not synonymous with economic significance, the economic magnitude of the relationship between tasks and wages—even net of other variables—is sizable. Within occupations, a one standard deviation increase in Abstract tasks predicts a 7 log point wage premium. A one standard deviation increase in Manual tasks predicts a 15 log point wage penalty (col. 6). When human capital and gender controls are also included (col. 7), these effects are diminished slightly but remain large and significant. Among these three measures, the Routine task variable proves least robust, losing significance when either human capital controls (col. 4) or occupation dummies (col. 6) are included.

One aspect of these results merits particular emphasis. The estimates in table 4 indicate that even within occupations, there are systematic differences in job tasks among workers who differ according to human capital, race, and gender. This pattern directly implies that job tasks must also be predictive of wages—since tasks are correlated with education, demo-

per se (or do not affect wages through tasks). We cannot dismiss this possibility out of hand, although we doubt that it is the primary explanation for the findings below.

graphics, and occupation, and these variables are in turn predictors of wages. What is not known from the prior results, however, is whether the residual variation in job tasks remaining after netting out occupation, education, race, and sex is also predictive of wages. Column 7 of table 5 reveals that this residual variation is indeed predictive of wages. These results indicate that self-reported job tasks capture substantive differences in job activities among workers, both within and between occupations.

B. Do PDII Task Measures Add Value to O*Net Task Measures?

A further means to assess the value added of the individual-level PDII measures is to compare their predictive power with the corresponding O*Net measures. In this section, we use the O*Net measures introduced in table 3, along with the PDII measures used in the prior two tables, to make this comparison. The first column of table 6 repeats the simple regression of wages on the Abstract, Routine, and Manual task measures from table 5. Here we cluster standard errors at the occupation rather than person level because we will also be using occupation-level means of PDII and O*Net variables as predictors.

In column 2, we replace the individual-level scales with PDII occupational means, following the O*Net approach.[23] These occupation-level scales are also highly significant predictors of earnings. When both person- and occupation-level task measures are entered simultaneously (col. 3), both sets of variables remain highly significant, and this remains true when human capital and demographic controls are added to the model (col. 4).[24] Notably, the *F*-value of the person-level task measures substantially exceeds the *F*-value of the occupation-level measures. Given that measurement error in tasks will generally be greater at the person level than at the occupation level, this pattern argues strongly that the person-level task measures are informative. Perhaps surprisingly, the person- and occupation-level relationships between job tasks and wages are quite similar for Abstract and Routine tasks across columns 1 and 2. The occupation-level Manual task measure is substantially attenuated, however, when the person-level Manual measure is included in column 3.[25]

[23] To avoid confounding the predictive power of occupational averages with the direct correlation between a worker's own tasks and wages, the PDII occupational mean assigned to each observation is a "leave-out" mean, equal to the grand mean of the task measure for all workers in the occupation except for the current worker.

[24] Demographic variables are included in table 6 in all columns that include human capital measures, but we do not report them to conserve space.

[25] The table reports tests of the joint hypothesis that the coefficient of each of the three person-level task measures is equal to the corresponding occupation-level measure. We further test these restrictions for each task measure separately and readily accept the null hypothesis for the Routine and Abstract measures in all specifications. Conversely, we always reject the null for the Manual task measure.

Table 6
OLS Wage Regressions of Log Hourly Wages on Task Measures from O*Net and PDII (at the Person and Occupation Level)

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
PDII Abstract (person level)	.20		.13	.09		.14		.11	.08
	(.03)		(.02)	(.02)		(.03)		(.02)	(.02)
PDII Routine (person level)	−.10		−.05	−.01		−.07		−.05	−.01
	(.02)		(.02)	(.02)		(.02)		(.02)	(.02)
PDII Manual (person level)	−.19		−.15	−.09		−.18		−.16	−.10
	(.02)		(.02)	(.02)		(.02)		(.02)	(.02)
PDII Abstract (occ mean)		.22	.12	.07			.14	.08	.04
		(.03)	(.03)	(.03)			(.03)	(.03)	(.02)
PDII Routine (occ mean)		−.08	−.06	−.02			−.05	−.05	−.02
		(.03)	(.03)	(.02)			(.03)	(.03)	(.03)
PDII Manual (occ mean)		−.10	−.01	−.01			−.10	−.03	−.01
		(.03)	(.03)	(.02)			(.03)	(.03)	(.03)
O*Net Abstract (occ mean)					.36	.22	.22	.17	.11
					(.04)	(.04)	(.04)	(.04)	(.04)
O*Net Routine (occ mean)					.01	.02	.03	.03	.02
					(.06)	(.05)	(.05)	(.04)	(.03)
O*Net Manual (occ level)					.06	.11	.10	.12	.06
					(.03)	(.03)	(.03)	(.03)	(.03)
Less than high school				.07					.08
				(.09)					(.09)
Some college				.06					.05
				(.04)					(.04)
College				.29					.26
				(.06)					(.05)
Postcollege				.44					.40
				(.07)					(.07)
Experience				.03					.03
				(.00)					(.00)
Experience^2/100				−.05					−.04
				(.01)					(.01)
Spanish language				−.44					−.39
				(.15)					(.15)
R-squared	.30	.27	.34	.46	.25	.37	.32	.38	.48
F(PDII person level)	69.2		25.0	14.5		35.4		22.5	13.3
p-value	.00		.00	.00		.00		.00	.00
F(PDII occ means)		44.4	9.1	3.8			17.2	4.5	1.6
p-value		.00	.00	.01			.00	.00	.19
F(Equality of PDII person- and occ-level coefs)			3.6	2.1				3.2	2.5
p-value			.01	.10				.02	.06
F(O*Net occ means)					38.4	12.8	11.0	9.1	3.4
p-value					.00	.00	.00	.00	.02
F(Education variables)				14.2					13.3
p-value				.00					.00

NOTE.—n = 1,333. Standard errors in parentheses are clustered on occupation (241 categories). All models include a constant and are weighted by sampling weights. Columns 4 and 9 additionally include dummies for female, black, Asian, and Hispanic. occ = occupation.

In columns 5–9 of table 6, we introduce the O*Net measures and compare their performance with the PDII scales. Column 5 shows that the standardized O*Net Abstract scale has a stronger effect on wages (0.36) than the parallel PDII Abstract scale calculated at the occupational level (0.22). But when both O*Net and PDII occupation-level scales are included in column 7, both coefficients remain large.

We find less comparability between the PDII and O*Net coefficients for the Routine and Manual measures. Both Routine measures are relatively small in magnitude and not highly robust. We find a similar pattern for the PDII and O*NET Manual task measure, with the PDII measure taking a negative sign and the O*Net measure taking a positive sign. In this case, the discrepancy in magnitudes is substantial, and the O*Net Manual measure proves robustly significant. One summary conclusion we draw from this exercise is that deriving comparable task measures from different survey instruments presents a substantial challenge.

More encouraging from the table is the fact that the PDII person- and occupation-level measures generally retain significance even conditional on inclusion of the O*Net task measures. As the *F*-tests of joint significance reported in the final rows of table 6 indicate, the PDII person-level measures are highly significant in all models, as are the O*Net occupation-level measures. The PDII occupation-level measures are also highly significant in all but the final specification, where human capital and demographic variables are included in the model along with all three sets of task measures.

One inference from this exercise is that mean PDII scores could potentially be usefully merged onto other data sets that lack detailed information about the task content of jobs, such as the Current Population Survey. But the results in tables 5 and 6 also underscore that this procedure would discard meaningful variation in job tasks that occurs within rather than between occupations. Indeed, the main takeaway of these wage models is that, relative to standard, occupation-level measures of job tasks, person-level task measures appear to add significant value in explaining worker outcomes.

V. Job Tasks and Wages: Testing the Model's Predictions

This section provides two exploratory tests of the primary implication of the conceptual model following the simple theoretical ideas outlined in Section I. The first implication that we test is that the returns to the task categories must negatively covary within occupations.[26] To implement this test, we first estimate separately by occupation the following OLS regression of workers' hourly wages on their task inputs:

[26] To simplify terminology but with no loss of generality, we also refer to an occupation's wage regression intercept as a "task return."

$$\ln w_{ij} = \alpha_j + \beta_{j1}\text{Abstract}_i + \beta_{j2}\text{Routine}_i + \beta_{j3}\text{Manual}_i + e_{ij}. \tag{12}$$

As noted above, for an occupation to be included in this exercise, it must contribute at least five wage observations to the PDII data set, yielding a sample of 91 occupations and 928 observations.[27]

Using the parameters obtained from estimating equation (12), we perform bivariate regressions of the elements of $\{\alpha_j, \beta_{j1}, \beta_{j2}, \beta_{j3}\}$ on one another, in all cases weighting by the sum of worker weights within an occupation:

$$\begin{aligned} &\hat{\beta}_{j1} = \alpha_1 + \gamma_1\hat{\beta}_{j2} + e_{12},\ \hat{\beta}_{j1} = \alpha_2 + \gamma_2\hat{\beta}_{j3} + e_{13}, \\ &\hat{\alpha}_j = \alpha_3 + \gamma_3\hat{\beta}_{j1} + e_{01},\ \hat{\alpha}_j = \alpha_4 + \gamma_4\hat{\beta}_{j2} + e_{02},\ \hat{\alpha}_j = \alpha_5 + \gamma_5\hat{\beta}_{j5} + e_{03}. \end{aligned} \tag{13}$$

The conceptual framework predicts that the point estimates for $\gamma_1, \ldots, \gamma_5$ will not be uniformly positive. More precisely, we expect that $\min\{\gamma_1, \ldots, \gamma_5\} < 0$.

Consistent with the model's theoretical prediction, we find a nonzero number of negative relationships among task returns within occupations (table 7). In general, occupations that have high returns to Abstract tasks have low returns to Manual and Routine tasks. Conversely, returns to Manual and Routine tasks are positively correlated across occupations. Columns 4–6 in table 7 indicate that occupations with high returns to Manual tasks have relatively low wage intercepts, whereas occupations with high returns to Abstract and Routine tasks have higher intercepts as well. Overall, of the six bivariate relationships in the table, three are negative, and one of these is highly significant.

While these patterns are supportive of the model, the prediction that at least one of the six coefficients in table 7 must be negative is minimally restrictive.[28] Indeed, half of the six coefficients in the table are positive, and these coefficients display a similar pattern of statistical significance to the three point estimates that are negative.

A second complementary implication of the Roy framework is that workers will positively self-select into occupations along at least one task

[27] There are four parameters to be estimated, and hence at least five observations are required to estimate the parameters plus standard errors.

[28] If the regression coefficients were drawn at random, and assuming that the standard errors have the appropriate size, we would anticipate that one in 40 (2.5%) point estimates would be negative and statistically significant at the 5% level or better. With six coefficients drawn at random, the chance of obtaining at least one negative and significant coefficient is equal to 14% ($1 - 0.975^6$). Thus, in the best case, our test would reject the null by chance in 15% of cases. One could also note, for example, that half of the coefficients in the table are positive and that these display a similar pattern of statistical significance to the negative point estimates. While this pattern is not at odds with the model, it underscores that the model places very modest restrictions on the pattern of coefficients.

Table 7
Bivariate Relationships among Regression Coefficients obtained from Occupation-Level Wage Regression Models: OLS Estimates

	Dependent Variable					
	b(Manual) (1)	b(Abstract) (2)	b(Routine) (3)	Intercept (4)	Intercept (5)	Intercept (6)
b(Abstract)	−.10			.73		
	(.09)			(.19)		
b(Routine)		−.16			.26	
		(.10)			(.19)	
b(Manual)			.31			−.72
			(.13)			(.24)
R-squared	.01	.03	.05	.14	.02	.09

NOTE.—n = 91. Each column in each panel corresponds to a separate OLS regression of the indicated coefficient estimate on the tabulated coefficients plus a constant (coefficient not reported). Standard errors are given in parentheses. Models are weighted by the sum of PDII sampling weights in each occupation. Coefficients used as regressions variables above are obtained from person-level regressions of log hourly wages on standardized PDII task input measures (Abstract, Routine, and Manual) and an intercept, where regressions are performed separately within each PDII occcupation that contains at least five observations (91 occupations total). Regressions are weighted by sum of PDII sampling weights in each occupation. Means and SDs of the variables used in these models are: b(Abstract) .07 (.47); b(Routine) −.02 (.51); b(Manual) −.15 (.39); intercept 3.02 (.93).

dimension. To test this prediction, we estimate an OLS wage model akin to equation (10) from the theory section that interacts workers' self-reported use of Abstract, Routine, and Manual tasks with the mean use of each task within their occupations. We anticipate that at least one of these three interaction terms will be significantly positive—and that more than one will be positive if selection takes the form of comparative but not absolute advantage.

The estimates in table 8 offer support for these predictions. Column 1, which augments our prior OLS wage model with occupation-level task means, indicates that wages are significantly higher in occupations that are intensive in Abstract tasks and significantly lower in occupations that are intensive in Routine tasks. When we add interactions between worker-level and occupational-level mean task use in column 2, a surprising pattern emerges: two of the three interaction terms (Routine × mean Routine, Manual × mean Manual) are positive, and the Routine interaction term is highly significant.[29] As indicated by the F-statistic at the bottom of the table, these three interaction terms are also jointly significant. This is particularly noteworthy given that the coefficients on both the worker and occupation measures of Routine and Manual task inputs are negative, likely reflecting the fact that Routine and Manual tasks are most prevalent

[29] The table 8 estimates differ slightly from the specification in table 6 in that we do not use "leave-out" means of occupation task measures in table 8. This has little substantive effect on the estimates but it does contribute to a slight increase in precision.

Table 8
OLS Wage Regressions with Interactions between Worker Task Use Intensity and Occupational Mean Task Use Intensity

	(1)	(2)	(3)	(4)	(5)	(6)
PDII Abstract (person level)	.07	.07	.08	.08	.06	.07
	(.02)	(.02)	(.02)	(.02)	(.02)	(.02)
PDII Routine (person level)	−.03	−.06	−.02	−.04	.00	−.02
	(.02)	(.02)	(.02)	(.02)	(.02)	(.02)
PDII Manual (person level)	−.15	−.14	−.14	−.13	−.09	−.09
	(.03)	(.03)	(.02)	(.03)	(.02)	(.02)
PDII Abstract (occ mean)	.18	.18	.14	.14	.10	.10
	(.04)	(.04)	(.04)	(.04)	(.03)	(.03)
PDII Routine (occ mean)	−.08	−.10	−.08	−.09	−.04	−.05
	(.03)	(.03)	(.03)	(.03)	(.03)	(.03)
PDII Manual (occ mean)	−.01	.02	−.03	−.01	−.01	.01
	(.03)	(.04)	(.04)	(.04)	(.03)	(.03)
PDII Abstract (person level) × PDII Abstract (occ mean)		−.01		−.01		−.01
		(.02)		(.02)		(.02)
PDII Routine (person level) × PDII Routine (occ mean)		.06		.05		.032
		(.02)		(.02)		(.016)
PDII Manual (person level) × PDII Manual (occ mean)		.03		.01		.01
		(.03)		(.03)		(.03)
Gender and race controls	No	No	Yes	Yes	Yes	Yes
Human capital controls	No	No	No	No	Yes	Yes
R-squared	.35	.36	.38	.39	.47	.47
F(interaction terms)		3.0		3.4		1.4
p-value		.03		.02		.24

NOTE.—n = 1,333. Standard errors in parentheses are clustered on occupation (241 categories). All models include a constant and are weighted by sampling weights. Gender and race controls are dummies for female, black, Asian, and Hispanic. Human capital controls are education dummies, experience, experience squared, and a Spanish-language dummy. occ = occupation.

in middle- and low-wage occupations. The pattern of results remains unaffected by the progressive addition of demographic and human capital controls in columns 3–6, confirming their robustness. The Routine interaction term remains negative and significant in all cases. These positive interaction terms are potentially consistent with the Roy model's implication that workers who are highly productive at a given set of tasks self-select into occupations that differentially reward those tasks.[30]

[30] In a separate analysis available from the authors, we replaced all of the PDII occupational task means with the corresponding task scales from O*Net. In these regression models, all three interactions between person-level task inputs and their corresponding occupational means were positive and jointly significant (although significance declines once we include demographic and human capital controls). Given the imperfect correspondence between the PDII and O*Net task measures, we place less weight on this test of the Roy model than on the prior estimates in table 8.

VI. Conclusions

This paper makes three contributions to the expanding empirical and theoretical literature that employs job tasks as a building block for conceptualizing and quantifying job skill demands. Drawing on original, representative survey data containing detailed measures of workers' job tasks, we document that job tasks vary substantially within (as well as between) occupations and we establish that variation in job tasks among workers in the same occupations is systematically related to their race, gender, and English-language proficiency. The most pronounced and systematic differences in job task activity are found for Spanish-language speakers, who perform substantially fewer analytic and interpersonal tasks and substantially more repetitive physical and cognitive tasks than equally educated workers in the same occupations. Notably, females perform substantially fewer analytic tasks and substantially more interpersonal and routine tasks than equally educated males, but this pattern is proximately accounted for by differences in the occupations in which males and females are employed.

The second contribution of the paper is to explore the degree to which person-level variation in job tasks is a robust predictor of wages. While it would be hypothetically possible that the systematic differences in self-reported job tasks that we find between demographic groups are primarily an artifact of group differences in response patterns, the wage analysis suggests that this is not the case. The tasks that workers perform on the job are significant predictors of their hourly wages, both between and within occupational, demographic, and education groups. Notably, worker-level measures remain powerful predictors of wages when occupation-level job task measures from both O*Net and the PDII survey are simultaneously included in regression models. Thus, job task measures effectively distinguish normally unobserved attributes of workers and jobs that vary within occupational, demographic, and education groups.

The third contribution of the paper is to offer a conceptual framework that makes explicit the links between workers' human capital endowments, their occupation, the tasks that they perform on the job, and the wages they earn. The simple observation that motivates our approach is that, while workers can hold multiple jobs, they can supply tasks to only one job at a time. The indivisible bundling of tasks within jobs means that the productivity of particular task inputs will not necessarily be equated across jobs—and so the "law of one price" will not generally apply to the market rewards to job tasks.

We propose a high-dimensional Roy framework in which the allocation of workers to tasks is driven by individuals self-selecting into occupations to maximize their incomes given their skill endowments. While this conceptual model is primarily intended to build intuition rather than guide empirical analysis, our exploratory empirical analysis provides some initial support for the conceptual model. In particular, we find evidence that (1) task returns vary across occupations in a manner that is consistent with competitive equilibrium and (2) worker self-selection into occupations takes a form that is consistent with comparative advantage.[31]

This evidence also has two main limitations. The first, emphasized above, is that these tests of the theory are not high powered. A second limitation is perhaps more fundamental: even if the evidence above were to constitute a definitive "existence proof" of self-selection in the labor market, our bare-bones model does not in its current form offer any deeper insight into the nature of self-selection that is operative. A richer model would potentially allow us to credibly characterize the variation in task returns across sectors and to study in detail the allocation of workers to tasks. This tool would be invaluable for forecasting how changes in task prices—catalyzed, for example, by automation or offshoring—may reshape the occupational assignments and earnings of different skill and demographic groups. We see a richer and more structured elaboration of this simple task approach as a promising avenue for further research.

Appendix

We used multi-item, additive scales from the O*Net database version 14.0 that were constructed by Acemoglu and Autor (2011) to evaluate the convergent validity of the PDII items and to assess the relative merits of person-level and occupation-level task measures. The names of the constructed scales are "Abstract," "Routine," and "Nonroutine Manual," and the O*Net items used in each are listed below.

1. Abstract

This scale is a standardized sum of the following two subscales:

A. Analytical

Analyzing data/information (Work Activities questionnaire, no. 9)
Thinking creatively (Work Activities questionnaire, no. 11)
Interpreting information for others (Work Activities questionnaire, no. 25)

B. Interpersonal

Establishing and maintaining personal relationships (Work Activities questionnaire, no. 28)

[31] More precisely, absolute advantage, which is a special case of comparative advantage (see n. 15).

Guiding, directing, and motivating subordinates (Work Activities questionnaire, no. 36)

Coaching and developing others (Work Activities questionnaire, no. 37)

2. Routine

This scale is a standardized sum of the following two subscales:

A. Cognitive

Importance of repeating the same tasks (Work Context questionnaire, no. 51)

Importance of being exact or accurate (Work Context questionnaire, no. 50)

Structured versus unstructured work (reverse) (Work Context questionnaire, no. 52)

B. Manual

Controlling machines and processes (Work Activities questionnaire, no. 18)

Keeping a pace set by machinery or equipment (Work Context questionnaire, no. 55)

Time spent making repetitive motions (Work Context questionnaire, no. 42)

3. Nonroutine Manual

Operating vehicles, mechanized devices, or equipment (Work Activities questionnaire, no. 20)

Time spent using hands to handle, control, or feel objects, tools, or controls (Work context questionnaire, no. 40)

Manual dexterity (Work Abilities questionnaire, no. 23)

Spatial orientation (Work Abilities questionnaire, no. 18)

Table A1
Means of Demographic, Human Capital, Earnings, and Occupation Measures for the Main Sample

	Mean	SD
A. Demographics:		
Age	39.37	12.62
Female	.47	.50
Spanish speaker	.05	.21
White non-Hispanic	.73	.45
Black non-Hispanic	.10	.30
Asian	.02	.14
Hispanic	.16	.37
B. Human capital and earnings:		
Less than high school	.09	.29
High school graduate	.31	.46
Some college	.25	.43
College or greater	.34	.47
Spanish speaker	.05	.21
Potential experience	19.57	12.36
Hourly wage	23.89	31.88
Log hourly wage	2.93	.66
C. Major occupation:		
Manager	.11	.32
Professional	.24	.42
Technical/sales	.12	.33
Clerical	.15	.35
Construction/repair	.07	.26
Production	.06	.23
Transportation	.07	.26
Service	.18	.39

NOTE.—n = 1,333.

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