From Tasks to Riches: A Task-based Approach to the Determinants of Wages

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An empirical investigation of the effects of occupational skills, human capital, and other worker characteristics on labor market outcomes is examined in this study. Using the PSA Labor Force Survey and Philippine Standard Occupational Classification (PSOC), the group offers a task-based measure as a proxy for occupational skills. Such problems in measuring skills arise when skill endowments of workers are underivable in a survey dataset. With this, the analysis includes comparing and contrasting models with task-based measures of occupational skills and Mincerian wage models with occupational dummies. Regression analysis found consistent statistically significant positive returns on a change in computational, ICT, and cognitive-interactive skills across occupations by 12%, 1.5%, and 3%, respectively.

1. INTRODUCTION

A growing body of knowledge on labor research suggests that firms have increasingly preferred compensating workers equipped with cognitive and interactive skills (Kobayashi & Yamamoto, 2020; Deming, 2017; Deming & Kahn, 2018; Autor & Handel, 2013). In the increasing global dependence on technology and capital-intensive ICT, skill price has widened between cognitive-interactive and manual skills in which low-skilled and blue-collar workers—whose occupational tasks generally require manual or physical skills—are among those affected.

In modern wage models, tasks are used as proxies for skills to observe the return on investment of skills to a worker's wage. Though the study primarily focuses on the supply side of labor in determining wages, it is acknowledged that wages are also affected by factors relating to the demand of labor (i.e., firms, shortages, job vacancies, etc.), which are not mostly captured in the model. With this, the group seeks to contribute to labor market research on skills and wages through a task-based approach. By creating a 10-task dimensional space, the group aims to (a) identify skill variables, (b) determine skill price to Filipino workers, (c) identify skill inequality in the labor market, (d) and compare the Mincerian wage models and task-based approach models. As the study has not been thoroughly explored in the Philippine setting, to achieve this, principal component analysis is used in identifying skills derived from the task dimensional space to develop models that explain the relationship between occupational skills and wages of workers using a dataset from Labor Force Survey Philippines.

2. LITERATURE REVIEW

The earliest forms of wage model literature were pioneered by Jacob Mincer, which he aptly named the Mincerian wage model (Lemieux, 2006). Heckman et al. (2006) also estimated Mincer rates of return by regressing the logarithmic form of wages on a panel data of years of schooling. This model has been widely used to represent wages as a function of years of education and labor market experience (Lemieux, 2006). Doing so, the model determines the return on investment of an individual's educational attainment and tenure measured as the years of experience. Even today, this framework is still being utilized in labor research, especially in estimating the value of certain human capital investment decisions. However, this model does not incorporate an important aspect in determining wages—a worker's skill.

Skills are an essential aspect of labor because it serves as an important dimension or indicator of employability as well as the wage determination of a worker. However, there has been difficulty in estimating the skills of a worker in previous literature. Modern-day databases cannot simply measure the skill of a worker, as skills are difficult to observe. Although skill databases like O*Net exist to measure skill requirements, these measurements are heavily based on self-reported skills, tasks, and occupational information. This greatly varies in terms of the detail and quality of the reported information by the employer and employee. This could pose a problem because tasks and skills based on personal judgments may result in either the overestimation or underestimation of the worker's skills. On a positive note, different literature offer other ways to measure skill. Hence, in modern labor studies, skill variables are usually measured as latent variables. Latent variables are variables that are not directly observed of a worker in the given dataset like a labor force survey; these variables are inferred through the use of statistical tools like principal component analysis or factor analysis derived from other variables that are present in the database.

Pioneered by Autor and Acemoglu (2011) task classification, several approaches in task-mapping in deriving occupational skills were developed. An example would be the task-dimensional approach in which this paper would be attempting to do. A task-dimensional framework uses a task framework consisting of several task dimensions as a proxy for skill to analyze its effects on wages. Each job comprises tasks and responsibilities that are not too different from the tasks of other jobs. Moreover, the task-based approach provides a basis for analyzing the similarity between all occupations in terms of the distance between them in the task complexity space (Gathmann & Schönberg, 2010). Using a factor analytic method like principal component analysis or factor analysis creates a component or skill variable that groups together tasks with the same or close variation and discredits tasks that are not significant in the variable altogether (Manzella et al., 2019; Dey & Lowenstein, 2019). This results in a unique measure of skill (skill score) for each occupation in the dataset.

Wages of occupations that require cognitive skills are comparatively higher than wages of low-skilled occupations. For example, mastery in terms of occupational tasks affects wages positively such that for occupations in sales, administrative, and service, cognitive and abstract tasks are more valued as manual tasks in blue-collar jobs. This is supported by Girsberger et al. (2018), in which productivity of cognitive skills paired with interpersonal skills is nearly twice as much as manual skills, resulting in larger returns for cognitive skills than non-cognitive skills. Consequently, tasks of higher-skilled occupations like professionals and managers involve income-generating and cost-reducing activities. Moreover, the cognitive skills of high-skilled workers are composed of analytical and interpersonal skills, which are complementary skills for these workers to be productive (Kracke & Rodrigues, 2020). These skills are highly incentivized by firms as these require higher levels of education, tenure, and human capital (Deming & Khan, 2018; Girsberger et al., 2018).

3. THEORETICAL FRAMEWORK

Job Tasks, Skill Endowments, and Wages

Tasks and skill endowments are both measures that represent the labor demand and supply factors relating to the skills of the worker, respectively. With those, Autor and Handel (2013) wrote the skill endowment of a worker in task k as a vector of innate abilities, human capital, or combination of both in performing a specific task k (Autor & Handel, 2013). Hence, the skill endowment of worker i is given as $\Phi_i = \{\Phi_{i1}, \Phi_{i2}, \Phi_{i3} \ldots, \Phi_{iK}\}$. Each element Φ_{ik} is positive considering the efficiency of worker i at task k from the worker's skill endowment (Autor & Handel, 2013). It is also worth mentioning that the skill endowments are unobservable variables in the data. However, in this framework, skill endowments are included in the analysis (Autor & Handel, 2013). The output of worker i at occupation j is given as:

$$Y_{ij} = e^{\alpha_j + \sum_K \lambda_{jk}\Phi_{ik} + \mu_i} \quad (1)$$

Logarithmic form of Y_{ij} is utilized to get the log wage of worker i represented as ω_i

$$log(Y_{ij}) = log(e^{\alpha_j + \sum_K \lambda_{jk}\Phi_{ik} + \mu_i}) \quad (2)$$

$$\omega_i = \alpha_j + \textstyle\sum_K \lambda_{jk}\Phi_{ik} + \mu_i \quad (3)$$

where α_j is the marginal productivity, which means that this variable can either be positive or negative because a worker with lower skills at performing task k may result in negative marginal productivity. $\sum_K$ *is* the summation operator of all tasks k, λ_{jk} is the returns of task k in occupation j, and μ_i is the error term of worker i (Autor & Handel, 2013).

$$\partial\omega_i / \partial\Phi_{ik} = \lambda_{jk} \quad (4)$$

This implies that skill endowments of worker i in doing task k results in the task returns of task k in occupation j. Thus, the returns to tasks can depend on the workers' skill endowments in performing tasks required in any occupation.

4. METHODOLOGY

To get the list of tasks of an occupation, we utilize the 2-digit sub-major group of occupations in 2012 PSOC and ISCO-88 job descriptions. Using this information, the 10 task-dimensional spaces (i.e., analyzing, creativity, information relaying, communication, guiding/developing others, computer, manual dexterity, spatial orientation, use of machine/controlling processes, and physical repetition) will be considered as the task variables wherein each task variable is evaluated using Autor and Acemoglu (2011) and Spitz-Oener (2006) keywords for classifying these tasks. In this method, we set the 10 task variables as a series of dummy variables. Each task variable has corresponding keywords that relate to the said task variable. The keywords that correspond to the spatial orientation task variable are manufacture, extract, manually processing items, mold materials, cook, and repair. Hence, a task variable for i = 1, 2, 3, …, 10 is set as 1 if at least one keyword is mentioned in the list of tasks of an occupation in the job description that corresponds to the task variable; 0 if no keyword is mentioned. Although the group originally planned to perform task mapping objectively using the Excel search function, this would result in unreported dummies in the task variable because several words are synonymous or relating to the keywords. For example, the task description of Scientific and Engineering associate (PSOC code 31) uses the term "conducting experiments"; instead of the term "research," which is indicated as a keyword for "analyzing" task variables. With this, the group simply performed task mapping manually.

After evaluating each occupation in the dataset along with the 10 task-dimensional space, the data will be processed through principal component analysis. The analysis of the 10 task variables (task-dimensional space) in the principal component analysis will be used to derive the skill variables or component variables which will then be integrated into the wage model. This is further explained in the next section.

The results have shown that the first three component variables resulted in a cumulative Eigenvector of 81.65%. This means that these three component variables or skill variables explain 81.65% of the total variation among the 10 task-dimensional space in the dataset. Arranged accordingly, these three positive components are cognitive-interactive, ICT, and computational skills.

Table 1

Factor Loading/ Scoring Coefficients from PCA

Task Variable	1st Compone nt	2nd Compone nt	3rd Compone nt
Analyzing	0.3420	0.2951	0.2614
Information Relaying	0.3298	-0.3705	0.2093
Creativity	0.3038	-0.0456	0.4897
Communication	0.3517	-0.2749	-0.0812
Guiding/developing others	0.2755	-0.6025	0.0725
Computer/database/ coding	0.2850	0.3892	-0.0393

Manual dexterity	-0.3664	-0.2556	-0.0188
Spatial Orientation	-0.3090	-0.0283	0.4960
Controlling processes /Use of machine	-0.2937	-0.0065	0.6094
Physical repetition	-0.2919	-0.3426	-0.1299

Note: 0.25 level of significance

Model Specifications

Using the cross-sectional data from the 2017/2018 Labor force survey dataset from PSA, we estimate our unrestricted wage model as:

$$\square\square\square\square\square\square_{\square} = \square_0 + CognitiveInteractive_i + ICT_i + Computational_i + \square_4 CognitiveInteractive_i^2 + \square_5 \square\square\square_{\square}^2 + \square_6 Computational_i^2 + \square\square_{\square} + \square\square_{\square} + \square\square_{\square} + \square_{\square}$$

Following the theoretical framework, the dependent variable, $\square\square\square\square\square\square\square_{\square}$, is the individual log of basic pay of a worker in the sample. The skill variables generated through PCA are cognitive-interactive, control processing skills, and supervisory skills. In Table 2, the group also integrated the squared of skill variables in the unrestricted and its subsequent models to determine the quadratic relationship between the skill variables and wages. The coefficients $\square_{\square}$ are a vector of other worker characteristic variables found in a typical Mincerian wage function. These variables are the following: (a) expected years of experience, which is taken from ADB calculation of worker's age subtracted by the starting labor force age of 15 years old; (b) squared of expected years of experience; and (c) years of education based on PSCED levels of education. $\square_{\square}$ is a vector of other worker characteristics such as the dummy variables of married, female, technical vocation, firm tenure, and urban. The coefficients of $\square_{\square}$ represent the effects of single-digit occupational dummies on the log wage of basic pay of a worker. Lastly, $\varepsilon_{\square}$ is the error term of the model. Below are the results of the regression analysis.

5. RESULTS

The series of regressions illustrated below provide several factors like skills, education, experience, occupation, and other worker characteristics that can statistically explain the logarithmic form of wages of workers. The group's regression design aims to create an unrestricted model with nested models of Mincerian wage models and the task-based approach models. The main difference between the two models is those skill variables and their quadratic forms are substituted with 1-digit occupational dummies in the task-based approach. Meanwhile, occupational dummies are integrated into the nested Mincer wage models and their succeeding models.

Table 2

Regression Results Log of Basic Pay Per Day as a Dependent Variable

Independent Variables	**Survey estimator: Ordinary Least Squares regression**		
	Task-based Approach Models	**Mincerian Wage models**	**Unrestricted**
	(1)	**(2)**	**(3)**
Cognitive-Interactive	0.029076*** (0.003382)		-0.040703*** (0.0049508)
ICT	0.014871*** (0.003347)		-0.055058*** (0.0056135)
Computational	0.114465*** (0.0042862)		0.05028*** (0.00538)
Cognitive □□□□□□□□	0.011231*** (0.0021249)		0.024178*** (0.0024461)
□□□^{2}	0.011589*** (0.0025738)		0.017158*** (0.0035365)
Compu□□□□	-0.008601** (0.0036648)		-0.00593 (0.0040527)
Schooling	0.060626*** (0.0011998)	0.041373*** (0.0011792)	0.043046*** (0.0011675)
Experience	0.018174*** (0.0012309)	0.014357*** (0.0011949)	0.014323*** (0.0011742)
□□□□□□□□□	-0.00029*** (0.0000242)	-0.000252*** (0.0000236)	-0.000249*** (0.0000232)
Technical Vocational	-0.009587 (0.0134999)	-0.010456 (0.0128448)	0.004528 (0.0128565)
Female	-0.175379*** (0.0081144)	-0.242286*** (0.0073649)	-0.174333*** (0.0077859)
Married	0.042608*** (0.0080461)	0.061423*** (0.007691)	0.051043*** (0.0074954)
Urban	0.192768*** (0.0076412)	0.172317*** (0.0073371)	0.191143*** (0.0072877)
Firm Tenure	0.136465*** (0.0087833)	0.099642*** (0.0085579)	0.108535*** (0.0084531)
1-digit Occupation dummies			
Managers		0 (omitted)	0 (omitted)
Professionals		0.224392*** (0.0309459)	0.248851*** (0.0319653)
Associate		-0.137666*** (0.032888)	0.013585 (0.0369864)
Clerical		-0.202246*** (0.0309749)	0.066509* (0.0362999)

Sales		-0.518541*** (0.0305285)	-0.45428*** (0.0327984)
Skilled Agriculture		-0.316243*** (0.618796)	-0.160162** (0.0660695)
Craft		-0.376782*** (0.0306268)	-0.307838*** (0.0439421)
Machine-Operator		-0.362596*** (0.0309725)	-0.283366*** (0.0472271)
Elementary		-0.611019*** (0.030663)	-0.524149*** (0.0461931)
Constant	4.826658*** (0.0268187)	5.597524*** (0.0362075)	5.290458*** (0.0538751)
Observations	37, 601	37, 601	37, 601
Number of PSU	24,407	24,407	24,407
Strata	2	2	2
Population size	23,752,550	23,752,550	23,752,550
Wald test: F-value	305.37***	106.00***	N/A
R-squared	0.4141	0.4591	0.4777

Note: Linearized Standard errors in parentheses. ***p < 0.01, **p < 0.05, *p < 0.10
For Wald test, prob > F. ***p < 0.01, **p < 0.05, *p < 0.10

Our findings do suggest that Mincerian wage models have more robust predictions on wages. However, a task-based approach model on determining wages offers a variable that is usually not considered in the analysis of wages because of the simplicity of labor survey databases, which is skills. The robustness check for OLS applied with sampling weights can only go so far as determining the adjusted Wald tests between the nested models and unrestricted model, evaluating R-squared, and evaluating coefficients of the variables in the model specifications. All things considered, we find that the task-based approach model and the Mincerian wage model as the final models in our analysis due to their relatively higher r-squared than their subsequent models. More importantly, both models have aspects of a worker's occupational choice, skills, education, experience, and other characteristics in explaining wages.

6. CONCLUSION

In the hopes of making a substantial contribution to previous literature, this study uses occupational tasks as a foundation for the conceptualization and the quantification of job skills in three ways. Drawing from the detailed list of tasks in the representative data, the group reports that job tasks within the same occupation classification will result in an identical profile of tasks in the dataset. However, wages may differ depending on the worker's labor experience, educational status, and other characteristics. It is established that the job tasks the group enumerated have some form of variation within those tasks. This resulted in the creation of component variables, which is the first contribution of this study to the expanding literature on the task-based approach to wages. Cognitive-interactive, ICT, and computational skills are identified as relevant skills in the analysis and their strictly positive impact on workers' wages. Building up from these skills, the second contribution of this paper to the existing literature is that there exists skill inequality between cognitive and non-cognitive skills in the labor market. Evidenced by the nature of the first component, cognitive-interactive skills and its quadratic form, and the wages of the workers suggest a relationship that is increasing at a faster rate. In Table 2, given that the opposite side of the first component is shown to have a high variation of tasks requiring manual skills, this regression analysis can be interpreted in reverse—a decrease in cognitive-interactive skills or an increase of manual skill by 1 results in wage penalties by the same coefficient. Lastly, the comparison between the Mincerian wage model and the task-based approach to wages has interesting results. Although the variance of independent variables that explain wages heavily favors the Mincerian wage models over the other—evidenced by its high r-squared—both unrestricted models are models that best fit to explain wages. The upside of the task-based approach model is that it adds another layer of dimension in explaining wages. It uses skills derived from tasks that are usually unobservable worker characteristics in labor market databases.

Because of the limitations in the Labor Force Survey dataset, the disaggregation of occupations such that jobs are more specific in the analysis is not possible. Using the 2-digit PSOC code from 2018, there were only 43 unique primary occupations included in the regression of data. Along with the limitations of primary occupations, the PSOC tasks list used in this paper to map out the given occupations was quite limited and outdated, with workers in the armed forces being excluded because of the lack of task description. Future empirical works should prioritize using a 3-digit PSOC code dataset to avoid further unobserved heterogeneity in the sample workers. Under these circumstances, further research on the task-based approach entails that there is a need for better measurements of skills and task requirements. This includes the use of mathematical and analytical tools to derive latent variables such as skills. At the same time, the inclusion of broader and technologically-based task variables to fit in the increasing demand for technological skills would be a preferable pursuit for further studies.

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