Folk Knowledge of the World of Work: Quantifying Perceptions of Occupational Attributes

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Abstract

A sample of labor market participants were asked to estimate the wage and projected employment growth for a selection of BLS occupations; they also reported whether they knew anyone working in that occupation. "Social" knowledge about an occupation—knowing someone working in that occupation—is associated with more accurate predictions of both the wages and future employment trends in that occupation, even when controlling for both the respondent and the occupation (respondents were asked about multiple occupations). At the occupation level, wage estimation and employment trend prediction errors are decreasing in the fraction of the population employed in that occupation. Respondents systematically underestimate the wages of higher-wage occupations, even when controlling for social knowledge. Managerial occupations are particularly pronounced outliers, with respondents strongly under-estimating the returns to being a manager. Respondent social knowledge is stratified by occupational hourly wage, with respondents knowing people in high-wage or low-wage occupations, but generally not both.

JEL J01, J24, J3

1 Introduction

To plan their careers, labor market participants should know what various occupations pay and the future prospects of those occupations. Misinformation about the current and future prospects of different careers could lead to poorly considered human capital decisions. This study assess the accuracy of career information held by a convenience sample of the US population—albeit one that is similar to the sub-population for whom accurate labor market information is most consequential. The main focus of the paper is on how occupational and individual characteristics mediate estimation accuracy.

For the 99 US occupations (as measured by the May 2013 OES) with the greatest employment totals, respondents from Amazon Mechanical Turk were asked whether: (1) they knew what the occupation consisted of (2) how many people they knew who held that occupation, if any, (3) their estimate of the hourly wage for that occupation and (4) whether in the future, wages and employment in that occupation would rise, fall or stay the same. There were no incentives for correct answers and the short time most workers spend on any tasks suggests they were not performing research.

*Author contact information, datasets and code are currently or will be available at http://www.john-joseph-horton.com/. Thanks to Alex Gedranovich for excellent research assistance.

Excluding some notable exceptions, respondents—at least collectively—demonstrated that they possessed substantial labor market knowledge: respondent mean estimates of hourly wages explain over 70% of the actual variation in wages. However, the residual variation was not idiosyncratic. Respondent predictions become less accurate the higher the wage for the occupation. In particular, respondents underestimate the wages of higher wage jobs. This is not simply because higher wage jobs are less common or that workers know fewer people with those occupations: controlling for the total employment in that occupation and whether the worker knows someone in that occupation, the negative relationship still exists.

Using fixed effects for both the worker and occupation, we show that knowing someone with a particulr occupation—"social knowledge"—reduces wage prediction error. Presumably wage information is just one dimension of occupational knowledge that gets passed along through social connections. If first-hand social knowledge is an important disseminator of labor market information, it suggests that isolated individuals exposed to a narrow slice of occupational possibilities could be at a labor market disadvantage. Social knowledge itself displays an interesting U-shaped pattern: workers know people with low wage jobs and high wage jobs, but know far fewer people in middle wage occupations. Respondent knowledge is also stratified by occupational income. Workers do not know about random subsets of occupations, but instead, knowing more high occupations makes it more likely that the respondent will know some other high wage occupation.

One concern with this study is that results from convenience samples do not necessarily generalize to the larger population. Even if they are representative, there is the unavoidable selection concern borne from the fact that the sample was recruited from an online marketplace. However, convience samples—beyond just being convenient—can given credible results for certain kinds of questions, particularly those trying to detect correlations. Laboratory economics experiments also use convenience samples under a similar logic. The epistemological justification in laboratory experiments that that even if "means" do not necessarily generalize—say the proportion of people in college or the magnitude of some treatment effect—correlations and directional relationships are more likely to hold generally.[1] While not guaranteed to be true, it does make findings about

One result that is both important and seemingly sensitive to the choice in population is the declining accuracy with increased wages. It is true that workers on Mechnical Turk are unrepresentative, in that they have lower than average wages (and tend to be younger), this is an advantage of this sample. However, given the motivation of the paper—assessing the accuracy of labor market information for would-be labor market participants faced with human capital decisions—this relative povery and youthfulness of the MTurk population is a plus.

If the patterns discovered here generalize, the good news is that they might be readily fixed: several studies have highlighted the powerful effects obtainable from purely informational interventions (e.g., Jensen (2010), Dupas (2009), Card et al. (2012)).[2]

Rees (1966) Stigler (1962) Hlavac (2013) for stargazer. Topel and Ward (1992) Pallais and Sands (2013) Burks et al. (2013) Betts (1996) Webbink and Hartog (2004) Dominitz and Manski (1996)

[1] For example, volunteers for a clinical trial presumably do not have hypertension at the same rate as the population, but if some drug can reduce levels of hypertension in a clinical trial, we suspect that directinal effect would also hold in the population.

[2] The connection between labor market information and allocative efficiency was in part the motivation for the Knowledge of the World of Work (KWW) test, which was briefly included in the NLSY (Kohen and Breinich, 1975).

2 Data collection and description

A total of 127 respondents participated in th survey. The respondents on average gaves responses for TK occupations; the median count of occupations was TK. Each occupation was estimated by TK different respondents. The actual survey interface presented to respondents in shown in Appendix A, Figure 4. The heading labeled would show the BLS occupation title.

For the social knowledge measure, respondents were asked how many individuals they knew in an occupation. The choices were 0, 1, 3 – 10 and more than 10. To construct a social index, these bins were coded as 0, 1, 2 and 3, respectively and then normalized.

3 Empirical Results

Our primary concern is whether respondents have correct beliefs about wages. Figure 1 is a scatter plot of the log actual wages (y-axis) versus the mean of log predicted wages (x-axis) for each occupation. Deviations from the 45 degree line indicate prediction errors. Outliers—both positive and negative—are labeled with the occupation title. There are two notable features of the data clearly illustrated by the the plot. First, it seems that workers systematically underestimate the wages of occupations at the high end of the distribution. Second, many of the extreme outliers are under-estimates of the wages of managerial occupations. The only occupation that workers substantially over-estimate is the home health aide category—perhaps becaus of a mistaken belief that this is the nursing occupation.

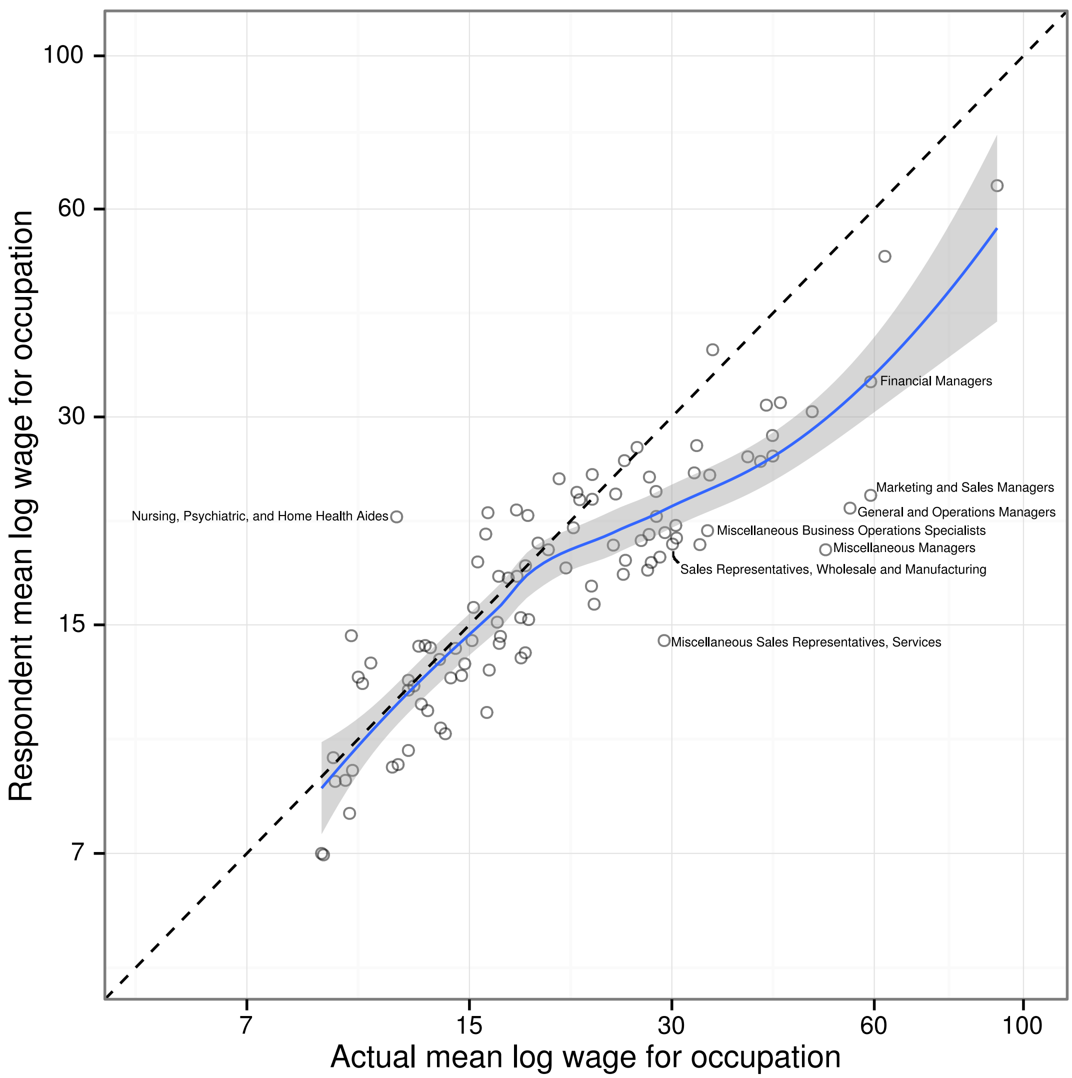
To explore the apparent systematic under-estimation of wages, in Figure 2 we plot the distribution of individual respondent log wage estimates for each occupation as a box plot. The actual mean and median wage for each occupation are shown as squares TK and triangles TK, respectively. Occupations are ordered by mean wage, from highest to lowest. By comparing the median of the boxplot to the actual median, we can see the tendency of respondents to systematically underestimate the wages at the high end of the distribution. The bias does not seem to be driven by high or low outliers that pull the mean away from the truth.

3.1 Determinants of the occupational knowledge and accuracy

Table 1 reports several regression where the outcome variable is the MSE in prediction, in log points. In Column (1), we can see, unsurprisingly, that prediction errors are decreasing in the total employment in that population. Column (2) adds as a predictor and indicator for whther the respondent knows that the job consists of. This is also negative, as expected, and lowers the employment coefficient. Column (3) adds the social index predictor, which is negative (albeit not significant) lowers the employment and job knowledge coefficients. Finally, in Column (4), we add the log mean hourly wage. It is strongly positive—consistent with our graphical evidence—and it also flips the sign of the employment coefficient. It also dramatically increases the adjusted R^2 of the regression. In the data, actual occupational wages and employment share have a strong negative correlation, which this sign-reversal reflects.

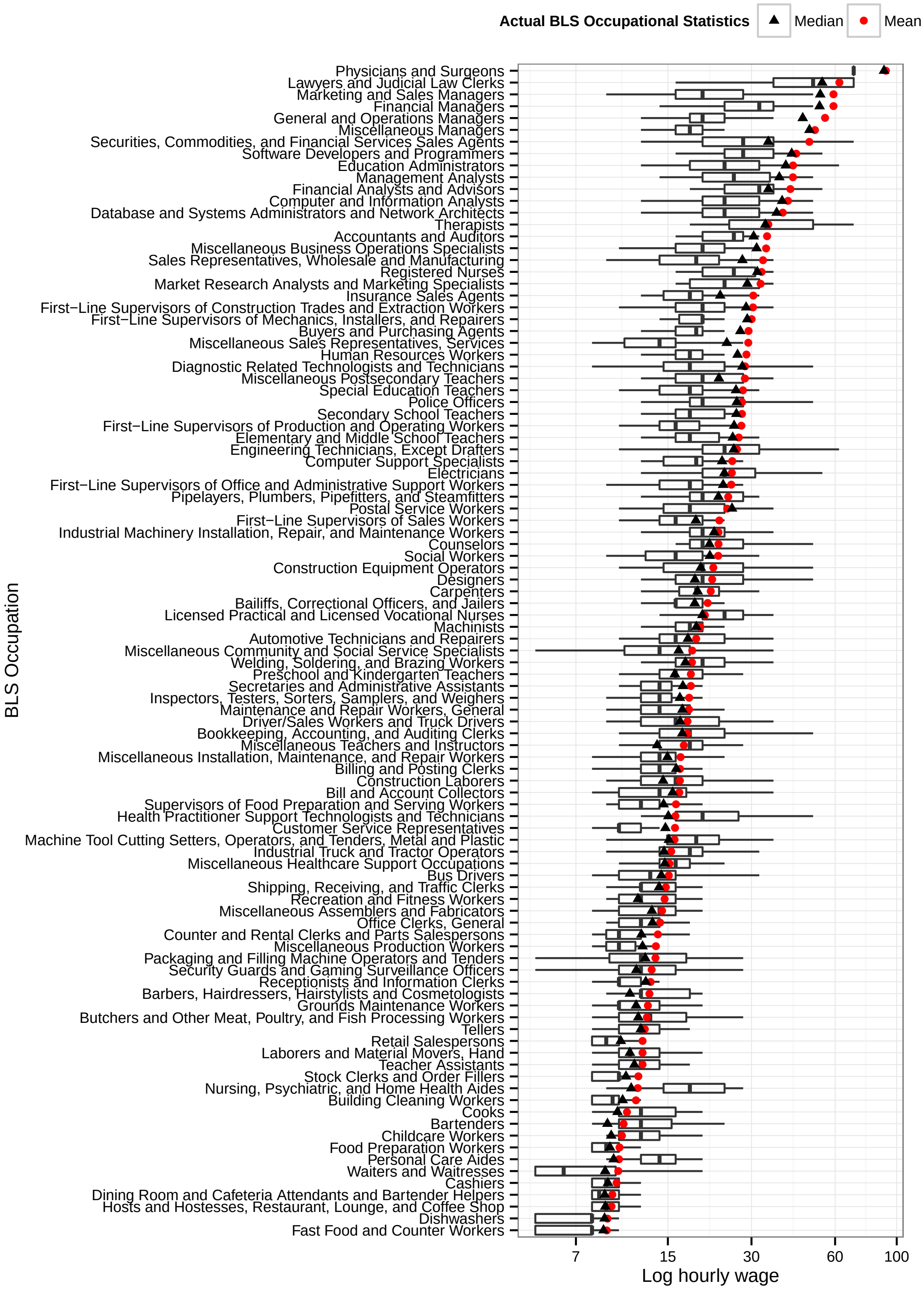
Given the strong effects that wage has on predictive accuracy, a natural question is how social knowledge and job knowledge vary with wage. Figure 3 plots the fraction of respondents reporting that they know what an occupation is (in TK) and whether they know someone with that occupation (in TK), binned by hourly wage. A clear U-shaped pattern is apparent: respondnents know more—both socially and substantiively—about low- and high-wage occupations, but less about the middle. This cuts against the idea that the population of respondents—which generally have low wages—simply does not know

Figure 1: Perceived hourly wages versus actual hourly wages



Notes: This plot shows the actual log mean wage versus the mean log wages versus predicted wages.

Figure 2: Distributions of respondent hourly wage perceptions by occupation



Notes: Boxplots of the respondent wage predictions are shown for each occupation. The actual mean is shown in TK, while the actual median is shown in TK.

Table 1: Occupation attributes and worker accuracy

	Dependent variable:					
	mse.wage			mse.v.trend		
	(1)	(2)	(3)	(4)	(5)	(6)
log(tot.emp)	−0.088	0.064	0.480	0.024	0.021	−0.016
	(0.081)	(0.065)	(0.381)	(0.043)	(0.045)	(0.265)
log(avg.wage)		0.720^{***}	2.698		−0.012	−0.187
		(0.088)	(1.788)		(0.061)	(1.242)
log(tot.emp):log(avg.wage)			−0.147			0.013
			(0.132)			(0.092)
Constant	1.196	-3.041^{**}	−8.667	0.413	0.486	0.983
	(1.104)	(0.995)	(5.175)	(0.584)	(0.687)	(3.595)
Observations	99	99	99	99	99	99
R^2	0.012	0.419	0.427	0.003	0.004	0.004

Notes: This table reports descriptive regressions where the depdendent variable is the MSE in respondent log wage prediction and the independent variables are the effects of social and general knowledge on a respondent's prediction error, while controlling for worker and occupation specfic effects. In Columns (1) and (2), the dependent variable is MSE in wage prediction, while in Columns (3) and (4), the dependent variable is an indicator for incorrectly predicting the direction of employment growth in that occupation. Columns (1) and (3) use worker and occupation fixed effects, with standard errors clustered at the level of the respondent (the more converative clustering choice), while in Columns (2) and (3), a multi-level model with respondent and title random effects are used. Significance indicators: $p \leq 0.05 : *$, $.p \leq 0.01 : **$ and $p \leq .001 : ***$.

Figure 3: Hourly wage and occupational knowledge

Notes: This figure shows the mean fraction of respondents either knowing someone or knowing what an occupation consists of, by hourly wage bands.

anyone at the top of the distribution. While the reason for the pattern in unclear, it could reflect frequent exposure to service occupations—both high and low-end—but relatively little exposure to managerial, trade and operational occupations that, as a matter of course, do not interact with individual consumers. Individuals are exposed regularly to low-wage jobs like waitresses and custodial workers and high-wage but professional jobs like doctors, dentists and lawyers, but they have little day-to-day experience with various managers, technical specialists, trade persons etc. that fill up the bulk of the mid-tier occupations.

3.2 Determinants of individual performance

In Table **??**, Column (1), we use the log points outcome measure, while in Column (2) we use the percentage outcome measure. Both regressions are fixed effect regressions, with fixed effects for both the respondnent and the occupation. We can see that social knowledge is associated with lower prediction error—in both specifications, social knowledge is negative and significant. Controlling for both the individual and the worker lets us isolate the effect of social knowledge. It is not the case—as it would be in cross-sections—that individuals with lots of social knowledge have reduced error rates or that occupations that are well-known socially also have little error. While social knowledge is of course not as good as randomly assigned—reverse causation—say having accurate beliefs about a particular occupation causes one to have friends with that occupation—seems implausible.

Table 2: Effects of social and general knowledge on occupational wage and trajectory estimate errors

	Dependent variable:			
	MSE Wage Error		Trend Error (1/0)	
	(1)	(2)	(3)	(4)
Social Knowledge Index	-0.028	-0.033^{**}	-0.047^{***}	-0.075^{***}
	(0.022)	(0.016)	(0.017)	(0.012)
General Knowledge Index	-0.004	-0.033	-0.025	0.045^{*}
	(0.037)	(0.031)	(0.031)	(0.025)
Worker FE	Yes	No	Yes	No
Occupation FE	Yes	No	Yes	No
Worker RE	No	Yes	No	Yes
Title RE	No	Yes	No	Yes
Observations	2,951	2,951	2,951	2,951
R^2	0.380		0.663	

Notes: This table reports the effects of social and general knowledge on a respondent's prediction error, while controlling for worker and occupation specfic effects. In Columns (1) and (2), the dependent variable is MSE in wage prediction, while in Columns (3) and (4), the dependent variable is an indicator for incorrectly predicting the direction of employment growth in that occupation. Columns (1) and (3) use worker and occupation fixed effects, with standard errors clustered at the level of the respondent (the more converative clustering choice), while in Columns (2) and (3), a multi-level model with respondent and title random effects are used. Significance indicators: $p \le 0.05 : *$, $.p \le 0.01 : **$ and $p \le .001 : ***$.

3.3 Stratification of knowledge

A important question is whether workers are stratified in their knowledge about wages. If workers only know about wages "locally" they might be stuck in a kind of trap, unwilling to make substantial human capital investments without more certainty about the reward. This possibility is even more important if drop-offs in knowledge are "steep" and if ignorance is increaes in wages—both patterns that exist in the survey.

We can test partially test this stratication proposition using our data, by seeing whether, for each occupation, social knowledge is predicted by the mean wages of the other occupations for which the worker claimed to have social knowledge. To fix ideas, consider an occupation, j. For that occupation, have an collection of individual wage estimates, $\hat{w}_{ij}$. For this measure, we compute $\bar{w}^{S}_{-j}$, which is the mean wage of other occupations for which the worker had social knowledge. We then regress:

$$Pr\{S_i = 1\} = \alpha + \beta \log w_i + \gamma \log \bar{w}^{S}_{-i} + \delta \log w_i \times \log \bar{w}^{S}_{-i} + \epsilon_{ij} \quad (1)$$

Table 3, we estimate Equation 1. As all our previous results have indicated, knowledge is decreasing in the wage of the occupation: $\hat{\beta}$ is negative. Consistent with the stratification hypotheses, the coefficient on the acutal wage and the social knowedge wage is positive, or $\hat{\delta} > 0$. Respondents that reported knowing people in higher-wage occupation where more likely to know someone in the ith occupation if the ith occupation was itself higher-wage.

4 Conclusion

This paper presents a number of results. First, respondents underestimate the wages paid at the high end of the wage distribution. This wage bias is knowledge does not seem to be driven by not knowing people with those occupations or misunderstanding of what those jobs consist of—these measures show a U-shaped pattern with respect to hourly wages, not a monotonically decreasing trend. One possible expanation for the relationship is that occupations at the high end are more likely to be salaried, which may weaken worker's ability to infer hourly wages.

To the extent that misperceptions affect career choices—or more probably—early human capital decisions—there is potentially an opportunity to improve market efficiency though a purely informational intervention. Respondents are particularly uninformed about the returns to being in a managerial occupation. If this holds more generally, workers might might place too little emphasis on moving up the internal labor market within their occupation. While we might expect workers within a firm to be more knowledgable about the returns to management, pervasive pay secrecy norms—particularly for management—might make this difficult.

Social knowledge of an occupation, i.e., knowing someone with that occupation, tends to reduce error. The relationship holds even with the include of both worker and occupation fixed effects. This rules out many selection-based stories for the explanation and suggests that knowing someone with an occupation can actually improve labor market knowledge. Although the effects of social relationships on error reducation are not absolutely large, presumably better wage information implies better, for more general occupational knowledge. As such, a useful career services intervention might be to exposure young labor market entrants or near entrants to a wider cross section of individuals in occupations—particularly mid-tier occupations that are in the valley of the U-shaped relationship in social knowedge that was discovered. This recomendation is further supported by the finding that social knowledge appears stratified by wage: workers knowing people in many high-wage occupations is more likley to know someone in some other high-wage occupation.

Table 3: General Knowledge Index, conditioned upon wages of other known occupations

	Dependent variable:	
	know.someone	fake.know.someone
	(1)	(2)
Actual occupation wage, $\log \bar{w}_i$	-1.593^{***}	-0.064
	(0.349)	(0.445)
Mean log wage of other known occupations, $\log \bar{w}^S_{-i}$	-4.464^{***}	-0.071
	(0.974)	(1.237)
Number of observations by worker, $\sum_i 1$	-0.001^{***}	-0.0001
	(0.0003)	(0.0003)
Interaction term: $\log \bar{w}_i \times \log \bar{w}^S_{-i}$	1.414^{***}	0.052
	(0.318)	(0.403)
Constant	5.575^{***}	0.575
	(1.068)	(1.364)
Observations	2,911	2,903
R^2	0.019	0.0002
Adjusted R^2	0.017	-0.001
Residual Std. Error	0.495 (df = 2906)	0.500 (df = 2898)
F Statistic	13.825^{***} (df = 4; 2906)	0.110 (df = 4; 2898)

Notes: TK This table reports the effects of social and general knowledge on a respondent's prediction error, while controlling for worker and occupation specfic effects. In Columns (1) and (2), the dependent variable is MSE in wage prediction, while in Columns (3) and (4), the dependent variable is an indicator for incorrectly predicting the direction of employment growth in that occupation. Columns (1) and (3) use worker and occupation fixed effects, with standard errors clustered at the level of the respondent (the more converative clustering choice), while in Columns (2) and (3), a multi-level model with respondent and title random effects are used. Significance indicators: $p \leq 0.05 : *$, $.p \leq 0.01 : **$ and $p \leq .001 : ***$.


Counter and Rental Clerks and Parts Salespersons
Miscellaneous Installation, Maintenance, and Repair Workers
Building Cleaning Workers
Tellers
Accountants and Auditors
Recreation and Fitness Workers
First–Line Supervisors of Production and Operating Workers
Miscellaneous Postsecondary Teachers
Social Workers
Industrial Machinery Installation, Repair, and Maintenance Workers
Miscellaneous Sales Representatives, Services
Stock Clerks and Order Fillers
Bookkeeping, Accounting, and Auditing Clerks
Miscellaneous Managers
Postal Service Workers
Sales Representatives, Wholesale and Manufacturing
Construction Equipment Operators
Electricians
Financial Analysts and Advisors
Bartenders
Lawyers and Judicial Law Clerks
Driver/Sales Workers and Truck Drivers
Preschool and Kindergarten Teachers
Construction Laborers
Registered Nurses
Cooks
Secretaries and Administrative Assistants
Customer Service Representatives
Police Officers
Barbers, Hairdressers, Hairstylists and Cosmetologists
Miscellaneous Teachers and Instructors
Elementary and Middle School Teachers
Licensed Practical and Licensed Vocational Nurses
Insurance Sales Agents
Grounds Maintenance Workers
Automotive Technicians and Repairers
Cashiers
Maintenance and Repair Workers, General
Personal Care Aides
First–Line Supervisors of Sales Workers
Miscellaneous Production Workers
Nursing, Psychiatric, and Home Health Aides
Machinists
Database and Systems Administrators and Network Architects
Carpenters
Computer and Information Analysts
Bailiffs, Correctional Officers, and Jailers
Marketing and Sales Managers
Waiters and Waitresses
Retail Salespersons
Computer Support Specialists
Childcare Workers
Secondary School Teachers
Special Education Teachers
Dining Room and Cafeteria Attendants and Bartender Helpers
General and Operations Managers
Office Clerks, General
Software Developers and Programmers
Receptionists and Information Clerks
Human Resources Workers
Fast Food and Counter Workers
Hosts and Hostesses, Restaurant, Lounge, and Coffee Shop
Engineering Technicians, Except Drafters
First–Line Supervisors of Mechanics, Installers, and Repairers
Bus Drivers
Bill and Account Collectors
Laborers and Material Movers, Hand
Machine Tool Cutting Setters, Operators, and Tenders, Metal and Plastic
Shipping, Receiving, and Traffic Clerks
Therapists
Miscellaneous Assemblers and Fabricators
Billing and Posting Clerks
Industrial Truck and Tractor Operators
Counselors
Physicians and Surgeons
Pipelayers, Plumbers, Pipefitters, and Steamfitters
Financial Managers
Security Guards and Gaming Surveillance Officers
Food Preparation Workers
Supervisors of Food Preparation and Serving Workers
First–Line Supervisors of Office and Administrative Support Workers
Dishwashers
Teacher Assistants
Welding, Soldering, and Brazing Workers
Securities, Commodities, and Financial Services Sales Agents
Buyers and Purchasing Agents
Designers
Education Administrators
First–Line Supervisors of Construction Trades and Extraction Workers
Health Practitioner Support Technologists and Technicians
Miscellaneous Healthcare Support Occupations
Diagnostic Related Technologists and Technicians
Inspectors, Testers, Sorters, Samplers, and Weighers
Miscellaneous Community and Social Service Specialists
Management Analysts
Packaging and Filling Machine Operators and Tenders
Miscellaneous Business Operations Specialists
Butchers and Other Meat, Poultry, and Fish Processing Workers
Market Research Analysts and Marketing Specialists

In terms of future work, the most obvious direction would be to try to move beyond the limitations of the sampling methodology. As as a starting point, some occupations could be evaluated with a nationally representative sample for whom demographic information is available, to at least provide a "stake in the ground" to see how strongly MTurk-results differ. Additionally, it would be useful to collect respondent income, education, labor market experience and gender and see how these factors mediate labor market information.

References

Betts, Julian R, "What do students know about wages? Evidence from a survey of undergraduates," *Journal of Human Resources*, 1996, pp. 27–56.

Burks, Stephen, Bo Cowgill, Mitchell Hoffman, and Michael Housman, "The Value of Hiring through Referrals," *Available at SSRN 2253738*, 2013.

Card, David, Alexandre Mas, Enrico Moretti, and Emmanuel Saez, "Inequality at Work: The Effect of Peer Salaries on Job Satisfaction," *American Economic Review*, 2012, *102* (6), 2981–3003.

Dominitz, Jeff and Charles F. Manski, "Eliciting Student Expectations of the Returns to Schooling," *The Journal of Human Resources*, 1996, *31* (1), pp. 1–26.

Dupas, Pascaline, "Do teenagers respond to HIV risk information? Evidence from a field experiment in Kenya," Technical Report, National Bureau of Economic Research 2009.

Hlavac, Marek, *stargazer: LaTeX code and ASCII text for well-formatted regression and summary statistics tables* Harvard University 2013. R package version 4.5.3.

Jensen, Robert, "The (perceived) returns to education and the demand for schooling," *The Quarterly Journal of Economics*, 2010, *125* (2), 515–548.

Kohen, Andrew I and Susan C Breinich, "Knowledge of the world of work: A test of occupational information for young men," *Journal of Vocational Behavior*, 1975, *6* (1), 133 – 144.

Pallais, Amanda and Emily Glassberg Sands, "Why the Referential Treatment? Evidence from Field Experiments on Referrals," Technical Report, Working Paper 2013.

Rees, Albert, "Information networks in labor markets," *The American Economic Review*, 1966, *56* (1/2), 559–566.

Stigler, George J, "Information in the labor market," *The Journal of Political Economy*, 1962, *70* (5), 94–105.

Topel, Robert H and Michael P Ward, "Job Mobility and the Careers of Young Men," *The Quarterly Journal of Economics*, May 1992, *107* (2), 439–79.

Webbink, Dinand and Joop Hartog, "Can students predict starting salaries? Yes!," *Economics of Education Review*, 2004, *23* (2), 103 – 113.

A Survey Materials

Figure 4 shows the actual survey interface used on Mechanical Turk.

B Occupational knowledge

In Figure 5, we plot the mean knowledge index by occupations.

Variable	Levels	n	Min	q_1	$\widetilde{x}$	$\bar{x}$	q_3	Max	s	IQR	#NA
Predicted Wage	Accountants and Auditors	28	16	20.0	26.0	24.7	28.0	32	5.3	8.0	0
	AutomotivTechniciansandReparrs	30	5	14.0	16.0	19.7	24.0	70	11.7	10.0	0
	Bailiffs,CrrctnlOffcrs,andJlrs	30	12	16.0	16.0	18.1	20.0	32	5.1	4.0	0
	Bartenders	30	5	10.0	12.0	12.3	15.5	24	4.5	5.5	0
	Bill and Account Collectors	30	8	10.0	14.0	15.1	17.5	36	6.7	7.5	0
	Billing and Posting Clerks	30	8	12.0	14.0	14.1	16.0	20	3.4	4.0	0
	Bookkpng,Accntng,andAdtngClrks	30	10	14.0	18.0	22.0	24.0	54	12.6	10.0	0
	Brbrs,Hrdrssrs,HrstylstsandCsm	29	5	12.0	12.0	14.0	18.0	20	4.0	6.0	0
	BtchrsandOthrMt,Pltry,andFshPW	30	8	10.0	13.0	14.0	17.5	28	4.7	7.5	0
	Building Cleaning Workers	30	5	8.0	9.5	9.3	10.0	16	2.9	2.0	0
	Bus Drivers	30	8	10.0	13.0	14.2	16.0	32	5.1	6.0	0
	Buyers and Purchasing Agents	30	10	16.0	19.0	20.4	20.0	54	8.1	4.0	0
	Carpenters	30	12	16.5	19.0	20.7	23.0	50	7.9	6.5	0
	Cashiers	29	5	8.0	9.0	8.9	10.0	16	2.0	2.0	0
	Childcare Workers	30	9	10.0	12.0	12.6	14.0	20	2.7	4.0	0
	CntrandRntlClrksandPrtsSlsprsn	30	5	9.0	10.0	10.4	12.0	18	3.0	3.0	0
	ComputerandInformationAnalysts	30	12	20.0	24.0	25.9	32.0	50	8.3	12.0	0
	Computer Support Specialists	30	12	14.5	19.0	18.6	20.0	28	4.8	5.5	0
	ConstructionEquipmentOperators	30	5	14.5	20.0	22.8	28.0	50	11.1	13.5	0
	Construction Laborers	30	9	12.0	16.0	17.6	20.0	36	7.2	8.0	0
	Cooks	29	8	10.0	12.0	13.2	16.0	20	3.9	6.0	0
	Counselors	29	16	18.0	20.0	24.8	28.0	70	11.6	10.0	0
	CustomerServiceRepresentatives	30	8	10.0	10.0	11.2	12.0	16	2.2	2.0	0
	Designers	30	12	16.0	20.0	23.3	28.0	50	8.4	12.0	0
	DignstcRltdTchnlgstsandTchncns	30	8	14.5	18.0	21.5	24.0	54	10.5	9.5	0
	Dishwashers	30	5	5.0	8.0	7.0	8.0	10	1.8	3.0	0
	DnngRmandCftrAttndntsandBrtndH	30	5	8.0	8.5	8.9	10.0	16	3.1	2.0	0
	Driver/SalesWorkrsandTrckDrvrs	30	9	12.0	16.0	17.6	23.0	36	6.3	11.0	0
	DtbsandSystmsAdmnstrtrsandNtwA	30	12	20.0	24.0	26.3	32.0	50	7.7	12.0	0
	Education Administrators	30	12	18.0	24.0	26.3	32.0	62	11.8	14.0	0
	Electricians	30	12	20.0	24.0	25.9	31.0	54	9.1	11.0	0
	ElementaryandMiddlSchoolTechrs	30	12	16.0	18.0	19.9	23.0	50	7.6	7.0	0
	EngineeringTchncns,ExcptDrftrs	30	9	20.0	24.0	27.1	32.0	62	11.5	12.0	0
	Fast Food and Counter Workers	30	5	5.0	8.0	7.0	8.0	10	1.7	3.0	0
	FinancialAnalystsandAdvisors	30	18	24.0	32.0	31.2	36.0	54	9.1	12.0	0
	Financial Managers	30	14	24.0	32.0	33.7	36.0	70	14.3	12.0	0
	First-LinSupervisorsofSlsWrkrs	29	10	14.0	16.0	16.1	20.0	24	3.5	6.0	0
	Food Preparation Workers	30	5	8.0	9.0	9.2	10.0	18	2.9	2.0	0
	Frst-LnSprvoMchncs,Instllrs,aR	30	9	16.5	20.0	19.6	20.0	36	5.8	3.5	0
	Frst-LnSprvsrsofCnstrctnTrdaEW	29	10	16.0	20.0	20.9	24.0	36	6.3	8.0	0
	Frst-LnSprvsrsofOffcandAdmnsSW	28	9	14.0	18.0	17.8	20.0	28	5.2	6.0	0
	Frst-LnSprvsrsofPrdctnandOprtW	30	10	14.0	16.0	18.0	19.5	50	7.7	5.5	0
	GeneralandOperationsManagers	30	12	18.0	20.0	22.1	24.0	36	6.0	6.0	0
	Grounds Maintenance Workers	29	8	10.0	10.0	11.5	14.0	20	3.1	4.0	0
	HlthPrcttnrSpprtTchnlgstsandTc	30	12	16.0	20.0	21.8	27.0	50	8.5	11.0	0

HstsandHstsss,Rstrnt,Lng,andCS	30	5	8.0	9.0	9.6	10.0	20	3.9	2.0	0
Human Resources Workers	30	10	16.0	18.0	18.8	20.0	36	5.8	4.0	0
IndstrlMchnryInstlltn,Rpr,anMW	30	12	18.0	20.0	22.8	24.0	50	9.3	6.0	0
IndustrialTruckandTractrOprtrs	30	9	14.0	18.0	18.5	20.0	36	6.9	6.0	0
Inspctrs,Tstrs,Srtrs,Smplrs,aW	30	5	12.0	14.0	13.4	15.5	20	3.7	3.5	0
Insurance Sales Agents	30	5	14.5	18.0	20.0	20.0	62	10.0	5.5	0
LaborersandMaterialMovers,Hand	30	8	10.0	11.0	12.5	14.0	24	4.0	4.0	0
LawyersandJudicialLawClerks	29	16	36.0	50.0	51.2	70.0	70	18.1	34.0	0
LicensdPrctclandLcnsdVctnlNrss	29	10	20.0	24.0	24.4	28.0	50	7.4	8.0	0
Machinists	30	10	16.0	18.0	19.3	20.0	32	5.1	4.0	0
MaintenancandRepairWorkrs,Gnrl	30	9	12.0	14.0	15.4	18.0	24	4.6	6.0	0
Management Analysts	30	14	20.0	26.0	28.2	35.0	50	9.0	15.0	0
Marketing and Sales Managers	30	9	16.0	20.0	23.1	28.0	50	10.2	12.0	0
MchnTlCSttrs,Oprtrs,aTndrs,MaP	30	9	15.0	19.0	20.3	23.0	36	7.4	8.0	0
MiscellaneosAssmblrsandFbrctrs	30	8	10.0	14.0	13.9	16.0	20	4.0	6.0	0
MiscellaneosBsnssOprtnsSpclsts	30	10	16.0	20.0	20.5	24.0	54	8.1	8.0	0
MiscellaneosHlthcrSpprtOccptns	29	5	14.0	16.0	15.9	18.0	24	4.3	4.0	0
MiscellaneosSlsRprsnttvs,Srvcs	30	5	10.5	14.0	14.2	16.0	28	5.0	5.5	0
Miscellaneous Managers	30	12	16.0	18.0	19.3	20.0	36	5.6	4.0	0
MiscellaneousPostsecondryTchrs	30	12	16.0	20.0	23.4	28.0	70	11.3	12.0	0
MiscellaneousProductionWorkers	30	5	9.0	10.0	10.6	11.5	28	4.3	2.5	0
MiscellaneousTchrsandInstrctrs	30	10	14.0	18.0	17.5	20.0	28	4.6	6.0	0
MrktRsrchAnlystsandMrktngSpcls	29	16	18.0	24.0	24.9	32.0	36	7.4	14.0	0
MscllnsCmmntyandSclSrvcSpclsts	30	5	10.5	14.0	15.3	18.0	36	6.1	7.5	0
MscllnsInstlltn,Mntnnc,andRprW	30	8	12.0	14.0	14.4	16.0	24	3.9	4.0	0
Nursing,Psychitrc,andHmHlthAds	30	9	14.5	18.0	21.5	24.0	70	13.0	9.5	0
Office Clerks, General	30	9	10.0	12.0	12.6	14.0	28	3.7	4.0	0
PckgngandFllngMchnOprtrsandTnd	30	5	9.2	12.0	13.4	17.5	28	5.6	8.2	0
Personal Care Aides	30	9	12.0	14.0	14.5	16.0	32	4.6	4.0	0
Physicians and Surgeons	30	32	70.0	70.0	64.9	70.0	70	11.7	0.0	0
Police Officers	29	12	18.0	20.0	24.6	28.0	50	9.8	10.0	0
Postal Service Workers	30	5	14.5	18.0	19.6	24.0	36	7.2	9.5	0
Pplyrs,Plmbrs,Ppfttrs,andStmft	30	12	18.0	20.0	23.2	28.0	62	9.2	10.0	0
PreschoolandKindergartenTechrs	30	10	14.0	16.0	18.3	20.0	50	7.6	6.0	0
ReceptionistsandInformatnClrks	30	8	10.0	10.0	11.3	12.0	18	2.2	2.0	0
Recreation and Fitness Workers	30	9	10.0	12.0	12.7	16.0	20	3.0	6.0	0
Registered Nurses	30	16	20.0	26.0	27.3	31.0	70	9.9	11.0	0
Retail Salespersons	30	5	8.0	9.0	9.9	10.0	20	2.8	2.0	0
SalsRprsnttvs,WhlslandMnfctrng	30	9	14.0	19.0	19.6	23.0	50	9.0	9.0	0
Scrts,Cmmdts,andFnnclSrvcsSlsA	30	12	20.0	28.0	30.5	36.0	70	16.0	16.0	0
Secondary School Teachers	29	12	16.0	18.0	20.3	24.0	54	8.2	8.0	0
SecretarisandAdmnstrtvAssstnts	30	10	12.0	14.0	13.7	15.5	20	2.9	3.5	0
SecrtyGrdsandGmngSrvllncOffcrs	30	5	10.0	12.0	13.9	16.0	28	4.9	6.0	0
Shipping,Recevng,andTrffcClrks	29	9	12.0	12.0	13.2	16.0	20	3.0	4.0	0
Social Workers	30	5	12.5	16.0	17.1	20.0	32	5.9	7.5	0
SoftwarDevelopersandProgrammrs	30	16	24.0	28.0	31.5	36.0	70	11.8	12.0	0
Special Education Teachers	30	10	14.0	18.0	18.5	20.0	32	5.2	6.0	0
SprvsrsofFdPrprtnandSrvngWrkrs	30	5	10.0	12.0	12.9	14.0	24	3.8	4.0	0
Stock Clerks and Order Fillers	29	5	8.0	10.0	9.4	10.0	16	2.6	2.0	0
Teacher Assistants	30	8	10.0	12.0	12.1	14.0	18	3.0	4.0	0
Tellers	30	8	10.0	12.0	12.2	14.0	18	2.6	4.0	0
Therapists	30	18	25.0	34.0	37.5	50.0	70	14.1	25.0	0
Waiters and Waitresses	30	5	5.0	6.5	8.0	9.8	20	3.9	4.8	0
Welding,Solderng,andBrzngWrkrs	30	12	16.0	20.0	21.6	24.0	36	6.5	8.0	0
all	2951	5	12.0	16.0	18.9	24.0	70	11.2	12.0	0

Table 4:

Figure 4: Survey questions

Answer Quuestions About Occupations

The job is: ${Title}

Do you know what doing this job consists of?

- Yes
- Maybe
- No

How many people do you know personally that do this job (if any)?

- 0
- 1
- 2
- 3 to 10
- More than 10

How much do you think this job pays per hour in the US, on average?

$7.00/hour

In the next 20 years, do you predict that the fraction of the working population doing this job will:

- Go down
- Stay the same
- Go up

In the next 20 years, do you predict wages for this job will:

- Go down
- Stay the same
- Go up

Any comments or questions?

Figure 5: General Knowledge Index by BLS occupation title

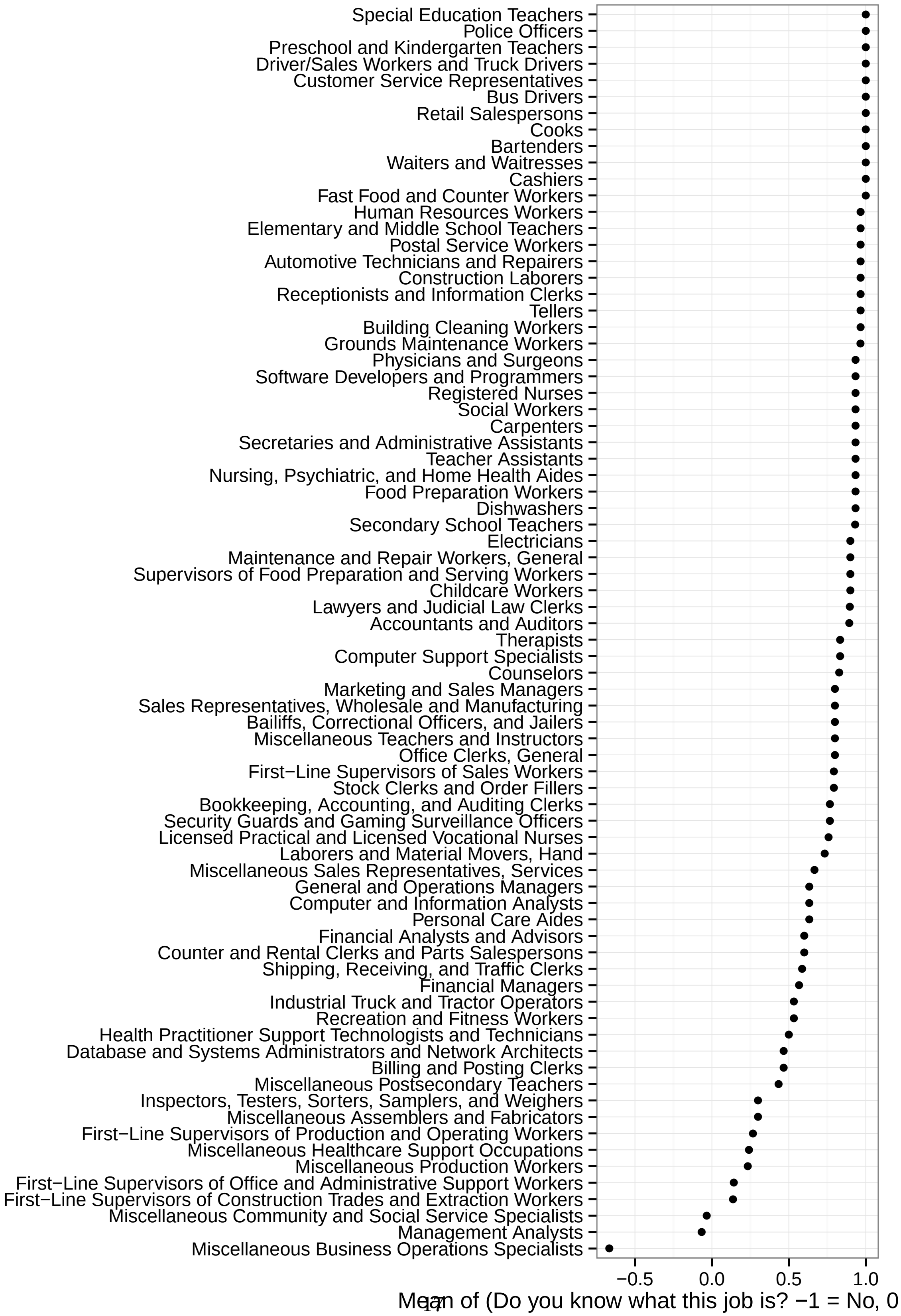


Figure 6: Social Knowledge Index by BLS occupation title