# Perceptions of Occupations: Good on Wages, Bad on Changes

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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 occupations; they also reported how many people they knew working in that occupation, which was used to create a "social knowledge" index. Collectively, respondents have good knowledge about wages—their wage estimates can explain more than 50% of the variation in actual log wages. And yet they know almost nothing about the direction of projected employment trends, with predictions about future employment being no better than chance. Despite poor overall predictions about employment trends, individual predictions were substantially improved if the respondent had better social knowledge about that occupation.

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 occupations could lead to poorly considered career and human capital decisions. This paper attempts to asses the quality of labor market knowledge held by a convenience sample of the US population drawn from Amazon Mechanical Turk (MTurk) by comparing their per-occupation estimates of wages and employment growth to the Bureau of Labor Statistics (BLS) estimates. The paper also attempts to understand how predictive accuracy is affected by "social knowledge" of that occupation, where social knowledge is an index based on how many people the respondent knows working in that occupation.

*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.

Collectively, the “wisdom of crowds” hypothesis seems to hold regarding wages: excluding some notable exceptions, the mean of estimates of wages were quite accurate. However, respondents did underestimate the wages of higher wage jobs, though it is unclear how much of this is due to the selected nature of respondents. Respondents were asked to say whether the fraction of people employed in an occupation will go up, go down or stay the same. Collectively, they do not better than chance when their answers are compared to the BLS projections. However, the more social knowledge a respondent has about an occupation, the better their prediction on the employment trend for that occupation.

The improvement in predictive accuracy from social knowledge is found despite our controlling for both the respondent and the occupation. These controls rule out the possible explanation that some occupations are easier to predict and many people know workers in those occupations; they also rule out the possible explanation that people with more social connections are better predictors. While still not causal, the non-causal channels for why social knowledge seems to improve predictive accuracy is far smaller than we had only cross-sectional data. The ability to include both kinds of controls illustrates an offsetting advantage to using MTurk: while still a convenience sample, MTurk provides a way to obtain a large number of responses even for a questionnaire that a “representative” sample would find tedious and be unlikely to complete carefully. This feature of MTurk is increasingly being used for questions in economics (Kuziemko et al., Forthcoming; Saez and Stantcheva, 2013).

There are conceptually similar papers to this one, but most of have focused on schooling decisions. For example, Dominitz and Manski (1996) elicited the returns to schooling from a convenience sample of high school students and undergraduates. Another example is Jensen (2010), which also focuses on returns to schooling, but includes an experimental information intervention that increased later schooling. General questions about the labor market—including some questions about various occupations—were part of the NLSY for a brief period (Knowledge of the World of Work (KWW) test) (Kohen and Breinich, 1975), though the nature of the questions was quite dissimilar to the questions asked in this paper. This is the first paper I am aware of that focuses explicitly on occupational knowledge.

There are lots of potential sources of knowledge about careers: career counselors, formal government statistics and informal channels like family and friends. There is a long-standing interest in how informal channels in labor markets affect outcomes(Rees, 1966; Stigler, 1962), but the very informality of these channels has made them difficult to study. However, interest in informal channels—particularly referrals—is going through a renaissance as it becomes easier to run experiments (Pallais and Sands, 2013) and obtain high-quality administrative data (Burks et al., 2013). This paper focuses on a social “stage” earlier than referrals by assessing how social connections mediate the knowledge needed to decide which opportunities to pursue. If the patterns discovered here generalize, gaps in knowledge might be readily fixed: several studies have highlighted the powerful effects obtainable from purely informational interventions (e.g., Dupas (2009), Card et al. (2012)). 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, contributing to inequality.

# 2 Data collection and description

For the top 100 US occupations by employment totals (as measured by the May 2013 OES), 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 employment in that occupation would rise, fall or stay the same.[1] The actual survey interface presented to respondents is shown in Appendix A, Figure 2. There were no incentives for correct answers and the short time most workers spent on any tasks suggests they were not performing research.

A total of 127 respondents participated in the survey. Each occupation was evaluated by 30 different respondents, though for my analysis I only used occupations where at least 20 out of the 30 respondents knew what the occupation was. I then further restricted the sample to only observations where the respondent knew what that occupation was. Appendix B contains descriptive statistics respondent knowledge about all occupations I originally included in the survey.

For "ground truth" on occupational wages, I simply used the estimated hourly mean wage from the OES. However, for occupations where hourly wages are not available, computed an estimated hourly wage based on a 40 hour week, for 50 weeks a year. For employment predictions, I took the 2010 employment level for each occupation and computed the fraction of the workforce in that occupation. I did the same using the 2020 employment projections. I then computed percentage changes for those occupations. I classified changes that were +/- 5% as "Stay the Same" (getting a value of 0) and those greater than 5% getting a value of 1 and those with a greater than 5% decrease getting a value of $-1$. The actual language of my survey question was "20 years" in the future. While this is not the period over which we have a BLS prediction, I worried that with too short of a time period many respondents would choose "Stay the same" and hence the request for a 20 year prediction.

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 with respect to the population of all responses across occupations.

# 3 Results

## 3.1 Predictions about wages and employment growth

To compare respondent predictions to BLS estimates, I simply regressed the BLS estimate on the associated respondent estimate. In Column (1), Table 1, the outcome variable is the log of the actual mean wage for the occupation. The regressor is the log of the respondent's wage estimate for that occupation. The regression includes an respondent-specific fixed-effect and standard errors are clustered at the level of the respondent. We can see that not only is the estimated wage highly significant and positive, the $R^2$ for the regression is quite high, with these

[1] http://www.bls.gov/oes/

estimates collectively explaining more than half the variation, even after the degrees of freedom correction.

Table 1: Predictions about wages and employment trends

| | *Dependent variable:* | |
|---|---|---|
| | Log Mean Occupational wage | Pred. Employment change |
| | (1) | (2) |
| Estimated log wage | 0.765*** | |
| | (0.023) | |
| Estimated employment change | | −0.030* |
| | | (0.013) |
| Respondent FE | Yes | Yes |
| Observations | 1,898 | 1,898 |
| $R^2$ | 0.569 | 0.059 |
| Adjusted $R^2$ | 0.540 | −0.004 |

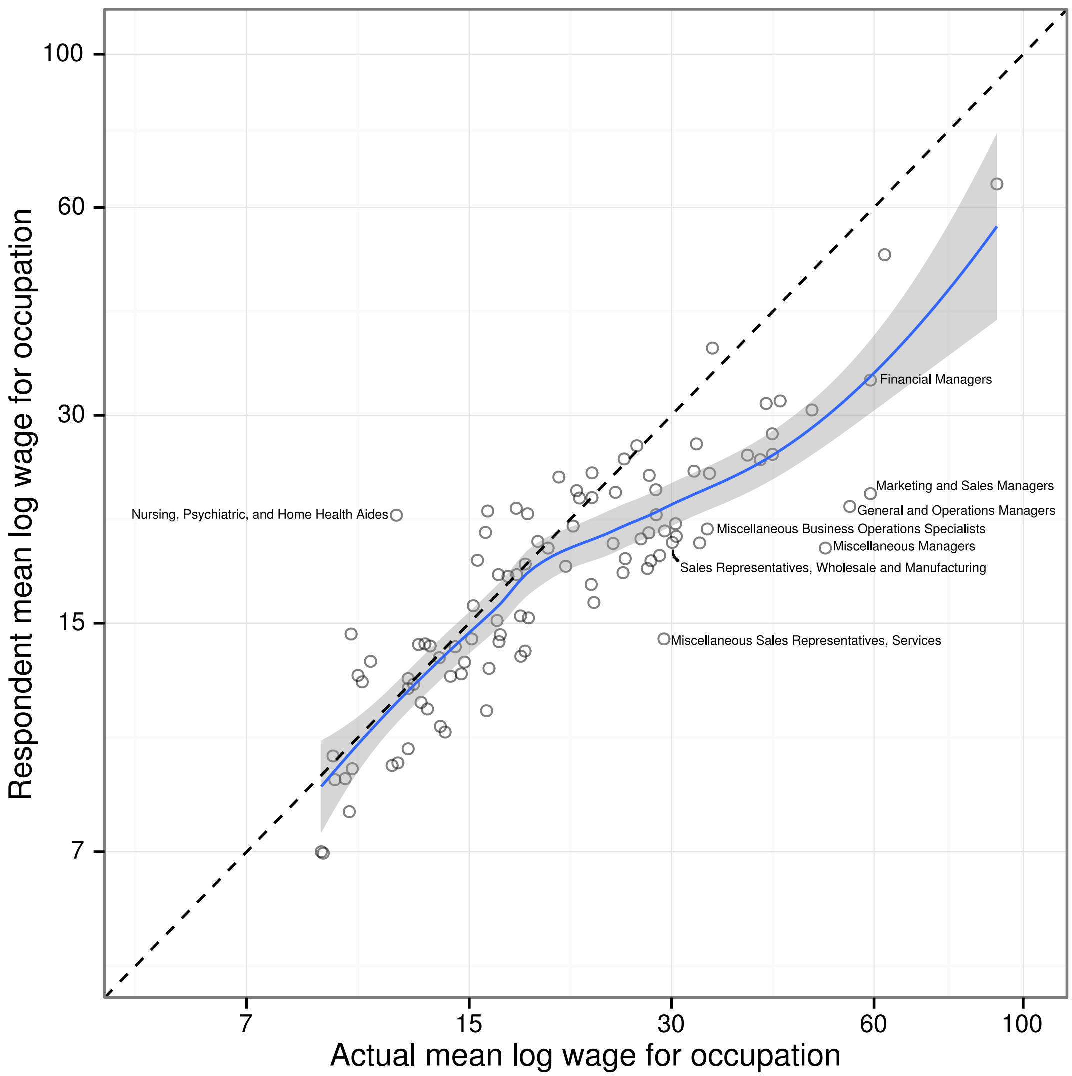
*Notes:* The sample for both regressions reported in this table are all the repsponses where the respondent said they knew what an occupation consisted of. In Column (1), the dependent variable is the actual log mean wage for that occupation (from the May 2013 OES estimates from the BLS), while in Column (2) the dependent variable is an index for whether the BLS predicts that by 2020 the fraction employed in that occupation will grow by more than 5% (outcome = 1), fall by more than 5% (outcome = -1) or will not change by more than 5%, positive or negative (outcome = 0). The important independent variable in both regressions is the respondent's prediction. Both regressions include a respondent-specific standard error. Standard errors are clustered at the level of the individual respondent. Significance indicators: $p \le 0.05 : *$, $.p \le 0.01 : **$ and $p \le .001 : ***$.

The regression approach masks a pattern in responses that is readily visible when actual wages are plotted against mean worker estimates. 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. There are two notable features of the data clearly illustrated by the the plot. We can see that respondents systematically underestimate the wages of occupations at the high end of the distribution.[2] Some outliers—both positive and negative—are labeled with the occupation title. Many of the extreme outliers are underestimates of the wages of managerial occupations.

In Column (2), Table 1, the outcome variable is the expected change in employment on the "Go Down" = -1„ "Stay the same" = 0, "Go up" = 1 scale and the independent variable is the respondent's prediction. As with the wage predictions, a respondent-specific fixed effect is included and standard errors are clustered at the respondent level. To the extent that the regres-

[2]The only occupation that workers substantially over-estimate is the home health aide category—perhaps because of a mistaken belief that this is the nursing occupation.

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.

sion has any predictive power, it is gained by *negatively* weighting predictions: in sharp contrast to the wage prediction results, there is essentially no relationship between BLS projections and individual projections.

## 3.2 Social knowledge and predictive accuracy

I now consider whether social knowledge of an occupation improves individual predictive accuracy. In Table 2, Column (1), the dependent variable is the respondent's prediction error in wages, defined as the absolute value in the difference in log wages between the respondent's estimate and the BLS value. In Table 2, Column (2), the dependent variable is the respondent's prediction error in employment trends, similarly defined as the absolute value in the difference in projects. For both regressions, both occupation- and respondent fixed-effects are included and standard errors are clustered at the respondent level.

Table 2: Social and errors in occupational wage and employment trajectories

| | *Dependent variable:* | |
|---|---|---|
| | Wage Error | Employment Trend Error |
| | (1) | (2) |
| Social Knowledge Index | −0.030 | $-0.054^{**}$ |
| | (0.025) | (0.019) |
| Respondent FE | Yes | Yes |
| Occupation FE | Yes | Yes |
| Observations | 1,898 | 1,898 |
| $R^2$ | 0.373 | 0.327 |
| Adjusted $R^2$ | 0.304 | 0.252 |

*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) the dependent variable is MSE in wage prediction, while in Column (2), the dependent variable is an indicator for incorrectly predicting the direction of employment growth in that occupation. Significance indicators: $p \leq 0.05 : *$, $.p \leq 0.01 : **$ and $p \leq .001 : ***$.

For wages, in Column (1), we can see that social knowledge is associated with reduced error, but the effect size is small and not significant. For project employment in Column (2), however, we can see that greater social knowledge is strongly associated with lower error in projected employment.

# 4 Discussion

One possible explanation for error in prediction for high-wage occupations is that occupations at the high end are more likely to be salaried, which may weaken workers' ability to infer hourly wages. Also, workers on Amazon Mechanical Turk tend to have lower than average wages and tend to be younger than the population at large (Ipeirotis, 2010). It is an open question whether this finding would generalize to the larger population.

The lack of predictive ability about employment trends is perhaps, ex post, unsurprising. Knowing employment trends for an occupation would require a fairly sophisticated understanding of long-term trends, such as the shift away from manufacturing and towards a service-based economy and the erosion of "middle skill jobs" (Autor et al., 1998). In contrast, learning the wages for an occupation is fairly straightforward.

What is surprising is that employment accuracy is apparently improved through social knowledge. In terms of mechanisms, for the social knowledge effects, it seems likely that knowing someone who works in an occupation would grant access to more nuanced views of an occupation: someone working in a particular field, especially one with some tenure, could probably explain how it was changing in terms of the accomplishment of the main work task, what new technologies were being used, where new sources of supply and demand were coming from and so on.

# 5 Conclusion

The main result of the paper is that respondents seem to have good knowledge about wages, at least collectively, but that their knowledge of projected employment—at least as predicted by the BLS—is very poor. However, social knowledge of an occupation, i.e., knowing someone with that occupation, tends to reduce predictive error about employment trends in that occupation, even when controlling for both the respondent and the occupation. By controlling for both the individual and the occuopation, we can plausibly 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 seems implausible: a reverse causation explanation would mean that accurate beliefs about a particular occupation causes one to have friends with someone in that occupation. As such, an intervention might be to expose young labor market entrants or near entrants to a wider cross section of individuals in occupations.

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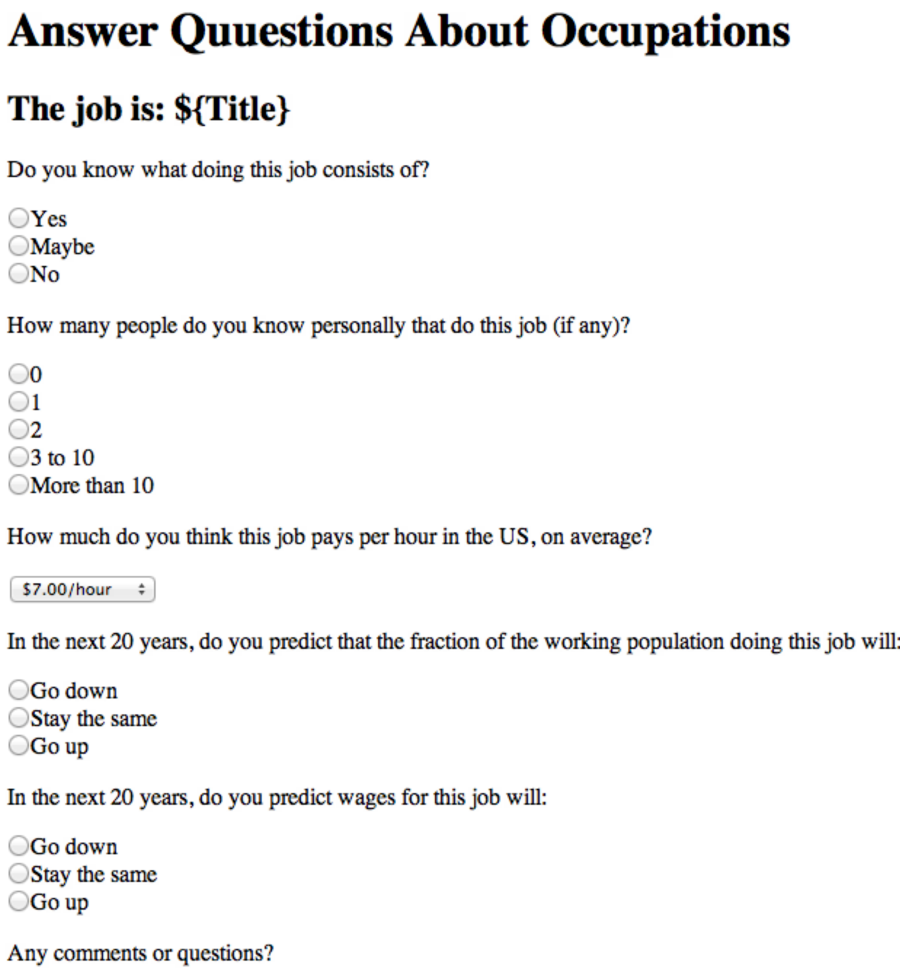
Figure 2: Survey questions


# 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?

# A Survey Materials

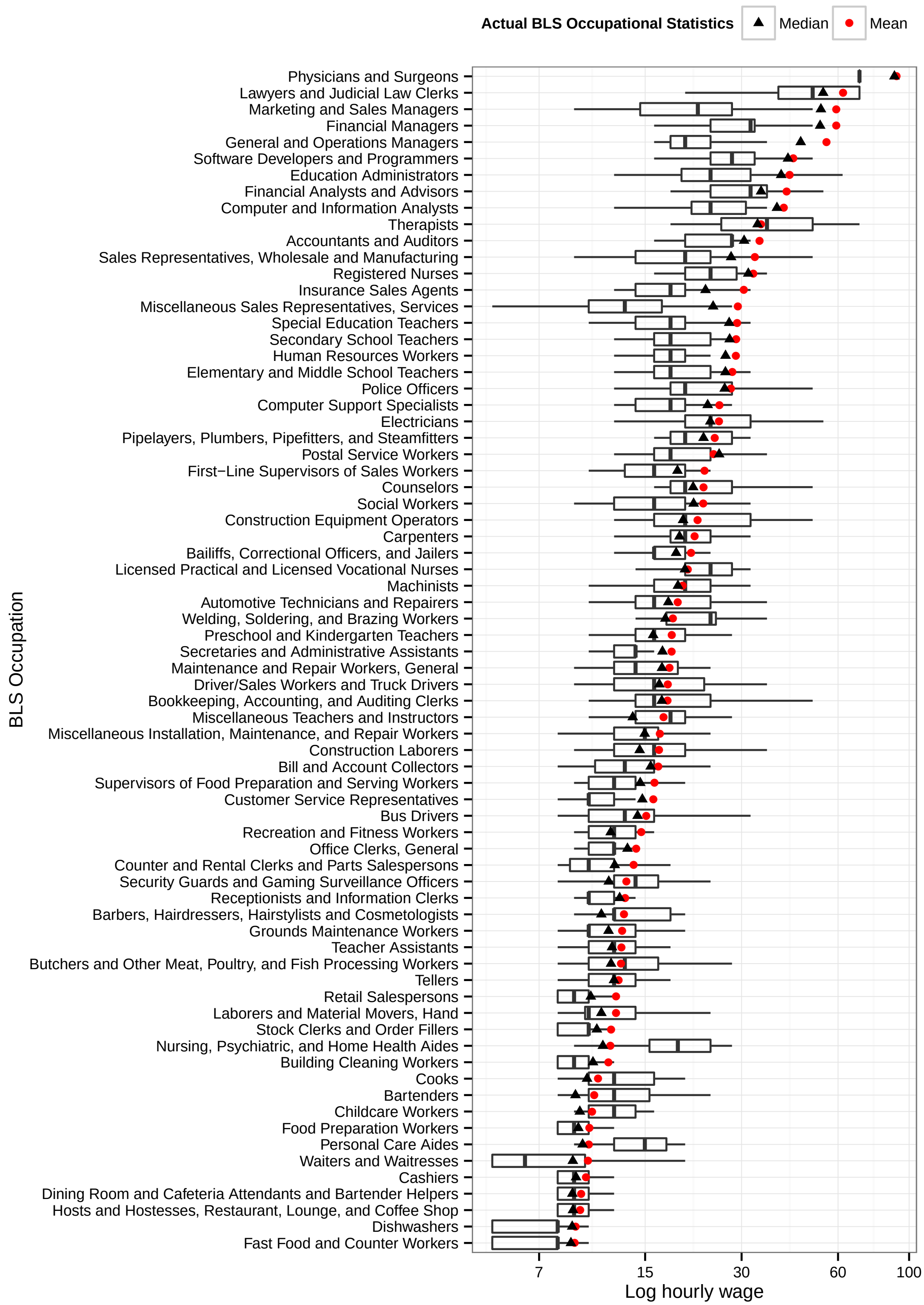
Figure 2 shows the actual survey interface. Wages in the drop-down box were listed in dollar increments from \$7 to \$10, two dollar increments from \$10 to \$20, four dollar increments from \$24 to \$36 and then six dollar increments to \$70/hour.

# B Additional data on occupational knowledge

Figure 3 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 and triangles, respectively. Occupations are ordered by mean wage, from highest to lowest. By comparing the median of the box plot to the actual median, we can see the tendency of respondents to systematically underestimate the wages at the high end of the distribution.

In Figure 4, we plot the mean knowledge index by occupations.

Figure 3: Distributions of respondent hourly wage perceptions by occupation




*Notes:* Boxplots of the respondent wage predictions are shown for each occupation, with actual mean and median over-layed.

Figure 4: General Knowledge Index by BLS occupation title

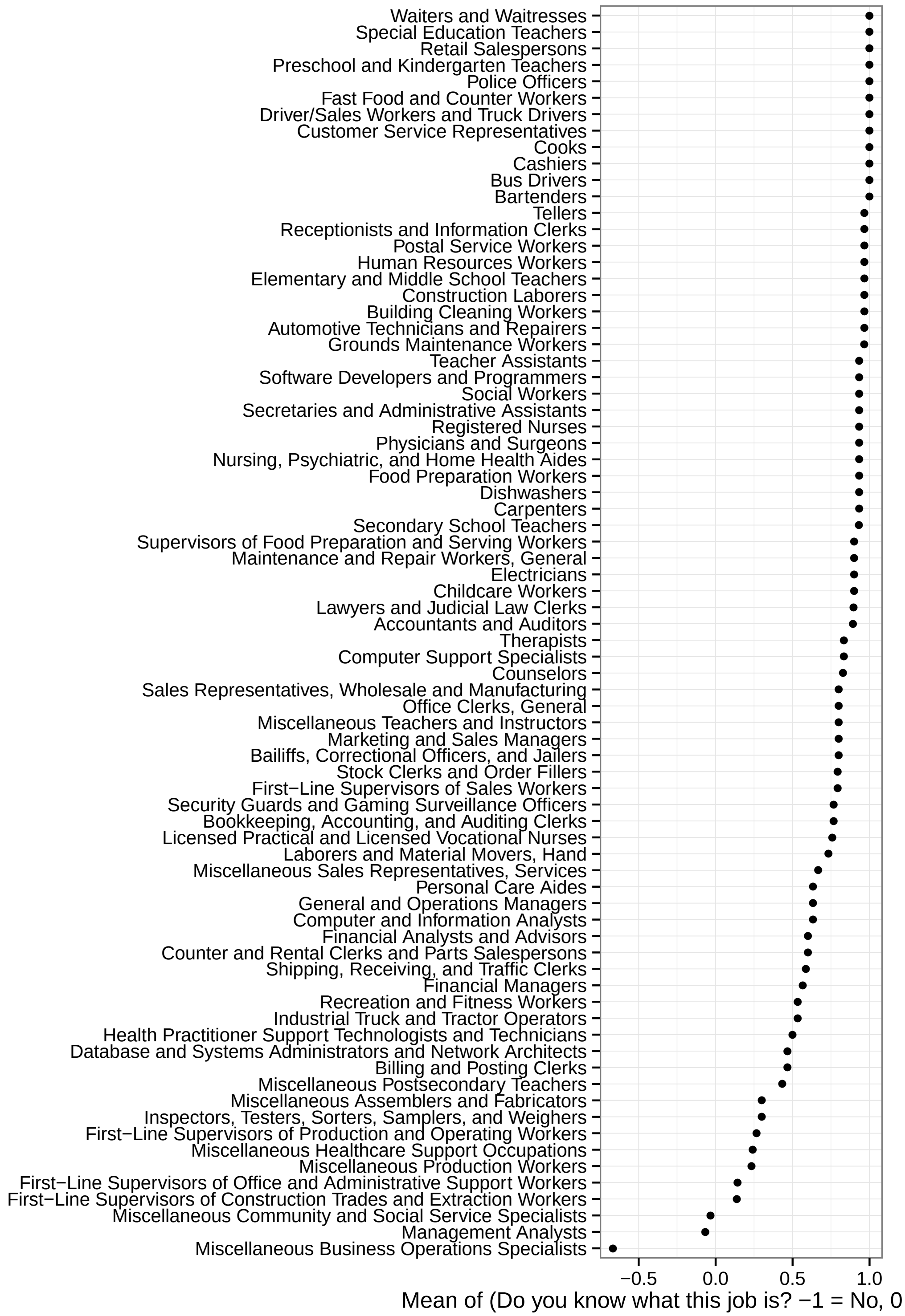


Figure 5: Social Knowledge Index by BLS occupation title