Wisdom of Crowds for Predicting Hot Jobs in the Near Future

Master Thesis

Xinying Xu

477272

Erasmus University Rotterdam, Erasmus School of Economics

August 10th, 2018

Abstract

Existing studies supply many instances of crowd wisdom in simple numerical cognitive problems. However, is the crowd still wise in consideration of complex realistic problems? Little research focuses on this situation. In this paper we investigated the wisdom of crowds on a daily topic: what are the Hot Jobs of the near future. Three research hypotheses are proposed to assist with the problem. Instead of directly using the ambiguous concept of Hot Jobs, we give it a statistical metric that consists of 3 components; high wages, strong projected growth and strong current demand. The data are collected from both survey and the Bureau of Labor Statistics (BLS). And then, we compare the outcomes between the crowd estimates with the top ranked estimates from BLS. We find that the crowd estimation on Hot Jobs in the near future can be wise when the estimative outcomes are measured by specific numerical information. Estimates of individuals are poor that only few people make correct forecastings. The study suggests that despite given a realistic complex problem, the crowd can still make a relatively good prediction without a complex aggregation approach.

Keywords: The crowd estimates, Hot Jobs, Job choice list, Comparison

1. Introduction

A well known British TV game show, named "*Who Wants to Be a Millionaire?"*, has two ways of seeking assistance; seeking help from an expert, or asking for help from the audience. Generally, experts are considered to be more knowledgeable than the audience. However, the audience tends to make right answers up to 91% of the time, while experts offer the right choice about 65% of the time. Thus, crowds can be considered to be wise and knowledgeable in making judgement and estimation.

The "wisdom of crowds" is the hypothesis that the collective opinion from a large group of people can be relatively more accurate than predictions of most single person in a lot of areas, including game shows, political elections, prediction market and forecasting (Surowiecki, 2004).

In this thesis, *what are the Hot Jobs of the near future*, a daily topic, will be chosen to clarify whether the crowd is able to make wise forecasts with regard to a series of realistic complex questions. Specifically, according to Bureau of Labor Statistics (BLS)[1], "Hot Jobs" refers to those jobs "in occupations that have strong projected growth and high wages and are in strong demand". This paper will adopt this definition to make further analysis.

Exploring the wisdom of crowds on forecasting Hot Jobs in the near future is practical and meaningful. Firstly, Hot Jobs forecasting is one kind of cognitive problem. Oxford English Dictionary (OED) defines the term cognition as "The action or faculty of knowing; knowledge, consciousness; acquaintance with a subject." Surowiecki (2004) wrote that crowds can perform well not only on realistic problems with right answers, but also on cognitive problems that are even complex and uncertain. Secondly, people are motivated to express their viewpoints and relevant knowledge regarding career planning and future prospects. Active expression is one of the constraints to produce crowd wisdom (Simmons et al., 2010). Thirdly, we can easily obtain diverse opinions of a crowd on the topic of Hot Jobs forecasting. Diversity is essential for adequate information within a group. Davis-Stober (2014) claimed that maximizing diversity of a crowd could make a crowd become the wisest. In addition, we ensure that all participants express their views independently. Random participants voluntarily join in the survey without any chance to communicate with each other. The crowd performance becomes worse by exchanging information within a group (Lorenz et al., 2011).

This thesis conducts a survey to collect the top five Hot Jobs forecasts of individuals, and to then aggregate the most mentioned ones as the forecasts of the crowd. Then, we compare the estimation results of the crowd with the BLS data and single respondents. The comparison of crowd estimates and individual estimates will be explored with and without job titles. The different approaches lead to completely different results. We also explored factors that have impact on the final estimation.

In the end, we conclude that the crowd can make good estimates at Hot Jobs in the near future to a certain extent. And the crowd estimates are obviously better than

[1] Source: https://www.bls.gov/

forecasting outcomes of individual. Both age and education are correlated with the right estimates of crowds.

This thesis contains 7 main chapters. The first chapter introduces the wisdom of crowds, including the implication of crowds wisdom and briefly summarizes the study. The second part is literature review and research hypotheses. The third chapter is methodology, which discusses the main methodology of this thesis. The next two chapters, data collection and analysis and results and hypotheses are the key part of the thesis, focusing on describing the data source and analyzing the survey results and 3 hypotheses elicited in the former text. The last part is the discussion and conclusion part, where results of this study and future directions are discussed in depth.

2. Literature review and research hypotheses

2.1 Literature review

Abundant studies and experiments find that the many are truly wiser than the single in simple numerical problems. As early as 1907, Galton hosted a quiz activity on guessing the dressed weight of an ox. 787 estimates gained from all participants. Galton found that by simply taking the arithmetic mean of all these estimative results, the aggregative weight is 1197 lbs, only 1 lb away from the real dressed weight 1198. And the median number from the crowd estimation is 1207 lbs, only overestimating by 0.8 percentages. Afterwards, a series of studies emerged. Two of the most classic experiment are the classroom temperature estimation by Knight (1921) and the bean jar experiments by Treynor (1987). Knight (1921) gathered a crowd of students to estimate current temperature of a classroom. The average estimate outcome is only 0.4 degrees away from the real temperature. Treynor (1987) put 850 beans in a jar, and the mean of crowds estimates is 871, while less than 2% individuals make a better estimate than the crowd.

Problems in real life are often complex and have no exactly correct answers. Arguments still exist on whether the crowd is wise on complex and uncertain cognitive problems. In the area of aesthetic tasks, the crowd performance is controversial. Mollick & R. (2015) claimed that crowds can make as successful decisions on simple aesthetic projects as the experts. More specifically, 93% projects selected by crowds succeeded, comparing with those selected by both crowds and experts. Görzen & Kundisch (2016) find the opposite result of a more complex task. They collected the crowd judgement of on a series of business model ideas via an online crowdvoting-platform. Both experts and anonymous crowd need to rate the given business model ideas based on creativity. In the end, the study reveals almost no correlation between these 80 participants judgement and two experts judgement, warning that the wisdom of crowds has limitation on relative complex problems. Brown (2015) suggests that public participation geographic information systems (PPGIS), a means to aggregate collective intelligence for land use decisions, can benefit planning outcomes.

According to the official concept of “Hot Jobs” from BLS, we first give “Hot Jobs” a statistical metric, which consists of 3 components: high wages, strong projected growth and strong current demand. The 3 components of Hot Jobs remain consistent from the beginning data collection to the end hypotheses analysis. In other words, survey participants are told in the survey that the BLS data is used to evaluate their forecasts. Subsequent hypotheses analysis compare the crowd estimates with BLS top 5 ranked jobs to further explore the wisdom of crowd.

This method is followed by Griffiths & Tenenbaum (2006), who compared a series of cognitive judgements of crowds on realistic problems rather than lab experiment with optimal statistical inferences of real-life data. The research suggests a closer correspondence between crowd judgement, which is based on common sense, and optimal statistical inference. Mozer et al. (2008) replicated Griffiths & Tenenbaum's work using different models, claiming that combining estimates over a crowd is able to achieve a good outcome relative to Bayesian perspective even if some individuals are innocent of the everyday phenomena.

Generally speaking, previous studies work in similar approaches, where two types of methods play important roles, one is taking unweighted arithmetic/geometric mean or taking the median (Galton 1907, Knight 1921, Lorenz et al. 2011) and another is majority rule (Treynor 1987). For instance, Lorenz et al. (2011) put a series of questions as population density, border length and number of new immigrants etc. in the study with consideration that it is reasonable efficient and unbiased to use unweighted arithmetic mean as a way to aggregate opinions of a crowd. Majority rule is also popular used as an aggregation approach to collect crowd opinions within a group of people. A Study of Hastie (2005) listed several properties of majority rule. One of the most useful properties of the majority rule is that it encourages people to express personal beliedfs more sincerely. The basic idea of majority rule is widely used in wisdom of crowds. Election and some prediction market experiments are typical manifestations. The simple method of aggregating collective information works as well as or even better than more complex strategies. (Mannes, Soll, & Larrick, 2014; Clemen, R. T. 1989).

2.2 Research hypotheses

Which factors may influence the crowd performance? Three research hypotheses are set to be explored in this thesis.

H1: The crowd can make a good estimation compared with BLS estimates.

In this hypothesis, crowds are considered to be wise if they can accurately predict one out of the BLS top 5 ranked jobs, or more than 50% of the BLS top 5 ranked jobs.

H2: The crowd can make better estimates on future Hot Jobs than estimates made by individuals.

Under this hypothesis, crowds are considered to be wiser than individuals if the aggregated forecast of crowds is closer to BLS top 5 ranked jobs than forecasting outcome of individuals.

H3: Which factors contribute to good or bad prediction of people on the future Hot Jobs?

In order to explore this hypothesis, personality information from survey is used to analyze correlations between people's correct prediction and personal characteristics.

3. Methodology

3.1 Aggregation methodology

In the real world, it can be difficult to obtain and aggregate opinion or judgement of crowds. On the one hand, people are not always good at or have sufficient motivation on expression and description, especially when confronted with unfamiliar, complex and inner feeling relative events. On the other hand, collective information is widely distributed among crowds around the world. In this modern internet connected world, the flow of information becomes much more efficient and faster than before. Just in Facebook, a social networking website, more than 2.2 billion monthly active users browsing or posting various information as of Q1 2018. 5.1 million comment, 2.93 million statuses and 1.36 million photographs are posted per minute. Therefore, in order to achieve primary goal of studies on the wisdom of crowd, a preset mechanism is essential to provide assists on people to speak out their judgement, estimation or opinions and on organism to aggregate crowds view successfully.

The existing studies in the area of collective intelligence mainly conduct research according to the following methodologies; mathematical aggregation, group deliberation and prediction market (Lyon & Pacuit, 2013).

Mathematical aggregation, the most popular method adopted by scholars, mainly focuses on arithmetic average and median. Galton (1907) is the first to conduct it regarding to collective intelligence outcomes. Specifically, he takes the mean and median from 787 estimates and finds that both figures are unbelievably very close to the true value. This method is continued to be used from then on. The experiment conducted by Knight (1921) that calls on students to make estimates on classroom temperature also works as simply taking average number.

Prediction market is a popular type of prediction mechanism based on collective intelligence. Researchers spend a lot of efforts on creating a real money oriented betting market with token or real money. The fluctuation of event price reflects the probability of event happening. The most famous prediction market is the Iowa Electronic Markets (IEM)[2], famous for predicting presidential elections. In addition to this, Hollywood stock exchange is a web-based betting market focusing on selling films or actor relative options and shares, and Good judgement is an prediction website including all kinds of political, financial and sports relative events.

3.2 Methodology implementation in the survey

We aggregate forecasting outcomes of the crowd by asking people to select top 5 jobs from a job choice list that best meet requirements of each question. The job choice list is created based on The Employment Projection program, a database of BLS that presents data on both historical and projected (2016-2026) employment by different constraints. We created the job choice list by taking top 20 jobs that have maximum values on three dimensions, (1) High wages, (2) Strong projected growth and (3) Strong current demands respectively. More specifically, jobs that repeat more than one time and are too similar to be distinguished are set to missing items. The next ranked items substitute the missing ones immediately.

[2] Source: https://iemweb.biz.uiowa.edu/

In the end, we gather 59 jobs, belonging to 18 occupations, in a list shown on Table I. The job choice list repeatedly appears in the 8 forecasting questions of the survey as random disorder to avoid order effects (Bradburn & Mason 1964, McFarland 1981).

Table I

Job Choice List

Occupation	Job	SOC_code
Management Occupations	Chief Executives	11-1011
	General and Operations Managers	11-1021
	Advertising, Promotions, and Marketing Managers	11-2000
	Sales Managers	11-2022
	Public Relations and Fundraising Managers	11-2031
	Financial Managers	11-3031
	Purchasing Managers, Buyers, Purchasing Agents	11-3061
	Compensation and Benefits Managers	11-3111
	Farmers, Ranchers, and Other Agricultural Managers	11-9013
	Architectural and Engineering Managers	11-9041
	Natural Sciences Managers	11-9121
Business and Financial Operations Occupations	Accountants and Auditors	13-2010
Computer and Mathematical Occupations	Computer and Information Research Scientists	15-1111
	Network and Computer Systems Administrators	15-1142
Architecture and Engineering Occupations	Aerospace Engineers	17-2011
	Computer Hardware Engineers	17-2060
	Petroleum Engineers	17-2171
Life, Physical, and Social Science Occupations	Physicists and Astronomers	19-2010
	Political Scientists	19-3094
Legal Occupations	Lawyers	23-1011
	Judges and Hearing Officers	23-1021
Educational Instruction and Library Occupations	Kindergarten and Elementary School Teachers	25-2012
	Teacher Assistants	25-9041
Healthcare Practitioners	Dentists	29-1020

and Technical Occupations	Pharmacists	29-1051
	Physicians and Surgeons Surgical Technologists	29-1060
	Anesthesiologists	29-1061
	Family and General Practitioners	29-1062
	Internists, General	29-1063
	Obstetricians and Gynecologists	29-1064
	Pediatricians, General	29-1065
	Psychiatrists, Psychiatric Technicians and Aides	29-1066
	Podiatrists	29-1081
	Registered Nurses	29-1141
	Nurse Anesthetists, Nurse Midwives, and Nurse Practitioners	29-1151
Healthcare Support Occupations	Home Health Aides and Personal Care Aides	31-1010
	Nursing Assistants and Orderlies	31-1014
Protective Service Occupations	Security Guards and Gaming Surveillance Officers	33-9030
Food Preparation and Serving Related Occupations	Cooks	35-1011
	Food Preparation Workers, Food and Beverage Serving and Related Workers	35-2000
	Waiters and Waitresses	35-3031
Building and Grounds Cleaning and Maintenance Occupations	Janitors and Building Cleaners	37-2010
	Maids and Housekeeping Cleaners	37-2012
	Landscaping and Grounds keeping Workers	37-3011
Personal Care and Service Occupations	Childcare Workers	39-9011
Sales and Related Occupations	Cashiers	41-2011
	Retail Salespersons	41-2031
	Sales Representatives, Wholesale and Manufacturing	41-4010
Office and Administrative Support Occupations	Bookkeeping, Accounting, and Auditing Clerks	43-3031
	Customer Service Representatives	43-4051
	Receptionists and Information Clerks	43-4171
	Stock Clerks and Order Fillers	43-5081
	Secretaries and Administrative Assistants	43-6010

	General Office Clerks	43-9061
Office and Administrative Support Occupations	Construction Laborers	47-2061
Installation, Maintenance, and Repair Occupations	General Maintenance and Repair Workers	49-1000
Transportation and Material Moving Occupations	Air Traffic Controllers	53-2021
	Heavy and Tractor-Trailer Truck Drivers	53-3032
	Hand Laborers and Material Movers	53-7060

4. Data collection and analysis

The process of analysis consists of 3 steps. At the beginning, making a definition of "Hot Jobs" as statistical as possible. Then, collecting BLS data and distribute the survey. Lastly, analyzing the data.

4.1 Concept of Hot Jobs

In this thesis, the concept of Hot Jobs is taken from BLS:

"Hot Jobs are those in occupations that have strong projected growth and high wages and are in strong demand."

In order to make a further statistical analysis on the concept of Hot Jobs, we break it into 3 component parts that I can use these 3 parts to make conditions for further application.

1) *High wages*. The salary is not only an important factor to measure the value of a job, but also the key consideration for people to seek or evaluate a job. High wage jobs are very attractive. Jobs with higher payment are usually more important, productive and high-level than jobs paid less. Judge & Bretz (1991) suggested that the salary is positively correlated to job satisfaction. People earns higher salary are considered to be more satisfied with the job. Comparing the salary among jobs by median wage is efficient because it is less likely to be influenced by extremely wages.

2) *Strong projected growth*. A hot job should be in a fast growing tendency and has great prospects, which lead to much more opportunities to achieve further development for individuals. The number of new jobs and the growing rate of new job, is a good measurement to forecast Hot Jobs.

3) *Strong current demand*. How many employees are employers seeking to hire? Which type of job is highly in demand? The current job shortage can reflect the statue of occupations. Data form the job market can help to answer these questions.

In the survey, we set 4 constraints according to the above 3 components of Hot Jobs. Median wages is used to measure high wages, a number of new jobs and a rate of growth for an occupation are used to measure strong projected growth and job postings is used to measure strong current demand. Both maximum and minimum values of each constraint are asked in the survey.

1) *Annual median wage*: The median annual salary of a given occupation, where half of the workers earned more and half earned less than.

2) *The number of New jobs*: The incresed or decreased number of jobs compared to last year. Occupations that already have large numbers of workers are usually expected to gain the most new workers.

3) *Growing rate of new jobs*: The rate indicates that in which percentage that the number of jobs of an given occupation is about to change. The larger the growing rate, the faster the job growth.

4) *Job postings*: The number indicates how many jobs in total employers are seeking to hire.

In the survey, questions are displayed as in the following examples:

- *In the following list, which 5 jobs do you think will have the highest median annual wage on June 1st 2018?*

- *In the following list, which 5 jobs do you think will have grown the least number of new jobs as of June 1st 2018 during the past 1 year?*

- *In the following list, which 5 jobs do you think will have the largest number of job postings on June 1st 2018 ?*

4.2 BLS data

The data of median wages, new jobs and rate of growth is from Occupational Employment Statistics (OES)[3], a program conducted by U.S. Bureau of Labor Statistics. The OES survey offers labor force data for more than 800 occupations and for the whole nation, including all states, metropolitan and nonmetropolitan areas. The database offers data not only on employment, but also on wages and more.

The data this thesis used is from the 2017 National Occupation Profiles. The data should be collected from database as of June 1st 2018. However, the May 2018 OES estimates will be published in spring 2019 while the May 2017 OES estimates have been published in spring 2018. This was unforeseen when planning the research design but the 2017 data can still be considered as a proxy for the 2018 data.

[3] Source: https://www.bls.gov/oes/tables.htm

The job posting data is from LinkedIn, a job posting network providing global information on current job demand. We typed job names into the search bar one by one. Finally, the number of job postings equals to the number of search results over the past 1 month as of June 1st 2018.

4.3 Survey

The survey contains 19 questions. 11 among them are personal detail basic questions, including questions on gender, age, nationality, identity, work experience related questions, career choice related questions and work ambition. The last 8 questions are main estimation questions referring to Hot Jobs: median wages, new jobs, rate of growth, and job postings.

The survey was distributed about half a month before June 1st 2018 and closed in the end of June 1st 2018. During the two weeks, questionnaires were distributed in two ways. The one is that we posted the survey link on several social networking webs like Wechat, WhatsApp, and Facebook. Another is that we directly invited people from public areas like public libraries, coffee shops and public parks to fill out the survey. All participants took the survey online by smart phones or computer. I invited 16 participants online and 5 people offline to take the survey. In the end, 96 individuals in total joined in the survey, 59 of them completed the whole survey, while the rest 37 were unable to finish all questions.

Table II

Respondents Profile

Characteristics		Distribution				
Gender		Female	Male			
	number	37	22			
	percentage	62.71%	37.29%			
Age		18-20 years old	21-23 years old	24-26 years old	27-29 years old	30 years or older
	number	2	30	15	6	6
	percentage	3.39%	50.85%	25.42%	10.17%	10.17%
Country		Asia	Europe	North America		
	number	50	8	1		
	percentage	84.75%	13.56%	1.69%		
Status		PhD student	Master student	Bachelor student	Working	Others
	number	3	31	9	13	3
	percentage	5.08%	52.54%	15.25%	22.03%	5.08%

Table II shows the description of total 59 respondents who finished all questions in the survey. 37 females and 22 males completed the whole survey, where most of them come from Asia, almost half of them are young people aged between 21 to 23 years old. Master students account for 52.54 percentages. The distribution shows that most participants are in their twenties; this is good because job estimation topics mostly concern teenagers and young adults. People's interests in the topics are beneficial to make the crowd estimation wiser (Simmons et al., 2010).

The attrition reaches up to 38.54% in terms of all participants. 37 participants opened the survey but failed to finish all questions, and 9 of them just click on the link without any responding, 14 of them were only able to complete some or all basic background questions, while the rest participants did answer all basic background questions but left more than one main estimation questions empty.

This high amount of attrition is within the expectation of survey design. Firstly, the survey follows anonymous and voluntary principles. Respondents can give up the survey due to any one of the questions at any time. Secondly, the survey does not provide incentives. Although proper incentives can give assistance on motivating respondents to put sufficient mental effort into the survey (Berk et al. 1987), simultaneously satisfying the two conditions, giving enough payment and saving survey cost, is difficult. Compared with the former background questions, the latter eight main estimation questions are difficult to answer and obviously need a lot of mental effort. This may explain the relatively low performance of the respondents.

5. Results and hypotheses analysis

This chapter is focusing on analyzing the 3 research hypotheses. The first hypothesis that the crowd can make a good estimation compared with BLS estimates is measured by two approaches: comparision on job titles and comparision on numerical information. The second hypothesis that the crowd can make better estimates on future Hot Jobs than estimates made by individuals is measured by statistical analysis. The last hypothesis that which factors contribute to good or bad prediction of people on the future Hot Jobs is measured by two regression modles. Analysis of the three hypotheses reveals that the prediction on Hot Jobs in the near future of the crowd are not only good but better than that of the individual. The correct forecasting outcomes of the crowd are influenced by age and education.

The collective intelligence is aggregated by tallying votes of each question. We first make a brief summarize of survey answers. Table III indicates the distribution characteristics of the final votes of each question. We compute the number of votes of 59 jobs from choice list based on each question and run the distribution related commands in Stata. The Standard deviation of questions on the minimum wage and minimum growing rate are higher than other values, suggesting that the crowd estimates on these two questions deviate further from the average outcomes. Skewness outcomes of all results are more than 0, indicating that the distribution of data is not symmetric, where questions of the minimum wage, the minimum growing rate appear to be more asymmetric relative to others. Kurtosis of all outcomes are all above 0, meaning that the crowd estimates distribute more weight at tails, especially on questions about wage, the minimum growing rate and the minimum job postings. The table indicates that the crowd estimates on each questions refer to Hot Jobs are not evenly distributed or centralized, but scattered in different items, meaning that participates have diverse and decentralized opinions (see Surowiecki, 2004).

Table III

The Distribution Characteristics of the Votes on Each Question

Questions	The highest median annual wage	The lowest median annual wage	The most number of new jobs	The least number of new jobs	The fastest number of growing rate	The slowest number of growing rate	The largest number of job postings	The smallest number of job postings
Std. Dev.	3.67	6.67	3.41	3.97	4.94	5.75	4.04	3.67
Variance	13.49	44.54	11.65	15.77	24.39	33.08	16.30	13.49
Skewness	1.73	1.92	0.68	1.07	1.43	2.03	1.43	1.73
Kurtosis	6.69	6.60	2.91	3.61	4.65	6.45	5.48	6.69

5.1 The crowd can make a good estimation

Table IV shows the final results of hot job estimation. The 5 jobs with most people voted for are collected in this table. The last three columns indicate aggregative estimates of the crowd, including job name, number of people who made the estimate, and the percentage of people who made the estimate respectively.

In this table, we define the crowd behave wise when at least one out five final estimative outcomes is the same as the BLS data estimates. Unfortunately, the table shows that the crowd is evidently unable to make a good estimation. There is no doubt that the crowd made an accurate estimate according to the BLS data only on jobs that have the lowest median annual wage with 31 out of 59 respondents. However, except for the only one correct forecast, the crowd performs unwise on the other 7 questions and therefore fails to make good prediction on future Hot Jobs. The table also shows that in terms of the most voted estimates, 6 out of 8 questions are supported by more than one-third of respondents, while 2 of which are even agreed with over half of individuals. Specifically, on the issue of high wage, growth rate and job postings, a fair number of people (more than one-third of respondents) selected the same jobs as their estimates. This fact indicates that there remains a tendency that the respondents have some similar ideas on these three kinds of questions even though the ideas are not accurate. The table results suggest that by comparing jobs with most votes with BLS word estimative outcomes sorted by exact job names, the crowd is unable to make good estimates on Hot Jobs in the near future.

Table IV

Final Top 5 Estimates Made by the Crowd and the Estimates of BLS

Constraints	Question	Estimation of BLS data	Estimates of the crowd		
			Estimation outcome	Number of people	Percentage (N/59)
Wages	The highest median annual wage	family and general practitioners	Chief Executives	34	57.63%
			Aerospace Engineers	25	42.37%
			Dentists	21	35.59%
			Computer Hardware Engineers	18	30.51%
			Computer and Information Research Scientists	17	28.81%
	The lowest median annual wage	waiters and waitresses	Waiters and Waitresses	31	52.54%
			Janitors and Building Cleaners	25	42.37%
			Maids and Housekeeping Cleaners	18	30.51%
			General Office Clerks	17	28.81%
			Landscaping and Grounds keeping Workers	16	27.12%
Projected growth	The most number of new jobs	Home Health Aides and Personal Care Aides	Computer Hardware Engineers	16	27.12%
			Advertising Promotions and Marketing Managers	16	27.12%
			Sales Managers	13	22.03%
			Childcare Workers	11	18.64%
			General Maintenance and Repair Workers	11	18.64%
	The least number of new jobs	Retail Salespersons	Judges and Hearing Officers	14	23.73%
			Political Scientists	12	20.34%

			Physicists and Astronomers	12	20.34%
			Cashiers	11	18.64%
			Aerospace Engineers	11	18.64%
Projected growth	The fastest number of growing rate	Home Health Aides and Personal Care Aides	Computer and Information Research Scientists	19	32.20%
			Computer Hardware Engineers	17	28.81%
			Childcare Workers	14	23.73%
			Network and Computer Systems Administrators	13	22.03%
			Advertising Promotions and Marketing Managers	10	16.95%
	The slowest number of growing rate	Computer Hardware Engineers	Political Scientists	18	30.51%
			Judges and Hearing Officers	16	27.12%
			Physicists and Astronomers	16	27.12%
			Hand Laborers and Material Movers	11	18.64%
			Cashiers	9	15.25%
Current demand	The largest number of job postings	Compensation and Benefits Managers	Waiters and Waitresses	21	35.59%
			Advertising Promotions and Marketing Managers	17	28.81%
			Sales Managers	17	28.81%
			General Office Clerks	16	27.12%
			Purchasing Managers Buyers and Purchasing Agents	12	20.34%
	The smallest number of job postings	Hand Laborers and Material	Physicists and Astronomers	25	42.37%
			Political Scientists	22	37.29%

Movers	Judges and Hearing Officers	20	33.90%
	Chief Executives	19	32.20%
	Air Traffic Controllers	16	27.12%

Table V shows the numerical comparison between the crowd estimate and BLS data regardless of job title. In this table, crowds are considered to be wise if they can accurately predict more than 50% of the BLS top 5 ranked jobs.

Table V

The Numerical Comparison between Crowds Estimation and BLS Estimation Regardless of Job Title

Constraints	Question	Estimation of the crowd	Estimation of BLS data	How many jobs have higher/lower outcome than crowd's forecasting			
				Higher		Lower	
Wages	The highest median wage	183270	198740	2	3.39%		
	The lowest median annual wage	20820	20820			0	0%
Projected growth	The most number of new jobs	-6180	558610	51	86.44%		
	The least number of new jobs	-60	-86460			17	28.81%
Projected growth	The fastest number of growing rate	0.0504	0.1443	5	8.47%		
	The slowest number of growing rate	-0.0047	-0.0847			14	23.73%
Current demand	The largest number of job postings	7954	586823	33	55.93%		
	The smallest number of job postings	1703	301			6	10.17%

Table VI

The Numerical Comparison between Crowds Estimation and Individual Estimation Regardless of Job Title

Constraints	Question	Estimation of the crowd	Mean estimation of individuals	Estimation of BLS data
Wages	The highest median wage	Chief Executives		Family and general practitioners
		183270	374281	198740
	The lowest median annual wage	waiters and waitresses	202857	waiters and waitresses
		20820		20820
Projected growth	The most number of new jobs	Computer Hardware Engineers		Home Health Aides and Personal Care Aides
		-6180	147038	558610
	The least number of new jobs	Judges and Hearing Officers		Retail Salespersons
		-60	75862	-86460
Projected growth	The fastest number of growing rate	Computer and Information Research Scientists		Home Health Aides and Personal Care Aides
		0.0504	0.0575	0.1443
	The slowest number of growing rate	Political Scientists		Computer Hardware Engineers
		-0.0047	0.0321	-0.0847
Current demand	The largest number of job postings	Waiters and Waitresses		Compensation and Benefits Managers
		7954	195156	586823
	The smallest number of job postings	Physicists and Astronomers		Hand Laborers and Material Movers
		1703	142481	301

The crowd estimates become more optimistic than in Table V. In terms of questions on wages, the crowd made an extremely wise estimate. Only 2 jobs have higher salary than the estimated job of the crowd. And the crowd estimate of the job with the lowest salary is accurate. The crowd also behaves wise on maximum growing rate and minimum job postings questions, only 5 and 6 jobs respectively perform closer outcomes according to requirements relative to BLS estimates. And the estimates of crowds on minimum new jobs and maximum growing rate questions are not bad. Less than 30% of jobs have better outcomes than crowd estimative jobs. Therefore, the crowd perform wise when the final estimation results are sorted by numerical information rather than ambiguous job titles, making good estimates in 6 out of 8 questions.

5.2 The crowd can make a better estimation on future Hot Jobs than individuals.

Table VI shows the numerical comparison outcomes between crowd estimation and individual estimation regardless of job title. The table aggregates the numerical information behind estimate outcomes of each respondent. The following expressions calculate the arithmetic average outcomes of all individuals' estimation results.

Average_Median_wage= $\sum_{i=1}^{n}(\mathrm{wage}_1 * \mathrm{job}_1 * x_1 + \mathrm{wage}_2\mathrm{job}_2 * x_2 + \cdots +$ $\mathrm{wage59job59}{*}\mathrm{x59}/(\mathrm{x1+x2+...+x59})$

Similarly, Number_of new_jobs=$\sum_{i=1}^{n}(\mathrm{new}_1 * \mathrm{job}_1 * x_1 + \mathrm{new}_2\mathrm{job}_2 * x_2 + \cdots +$ $\mathrm{new59job59}{*}\mathrm{x59}/(\mathrm{x1+x2+...+x59})$

Growing_rate=$\sum_{i=1}^{n}(\mathrm{rate}_1 * \mathrm{job}_1 * x_1 + \mathrm{rate}_2\mathrm{job}_2 * x_2 + \cdots + \mathrm{rate}_{59}\mathrm{job}_{59} * x_{59}) /$ $(x_1 + x_2 + \cdots + x_{59})$

And Posting_Number= $\sum_{i=1}^{n}(\mathrm{posting}_1 * \mathrm{job}_1 * x_1 + \mathrm{posting}_2\mathrm{job}_2 * x_2 + \cdots +$ $\mathrm{posting59job59}{*}\mathrm{x59}/(\mathrm{x1+x2+...+x59})$

Where wage_i is the median annual wage of each job, x_i is the mentioned times of job_i according to maximal or minimal requirements, new_i refers to the number of job growth, rate_i is growing rate of every jobs, and $\mathrm{posting}_i$ is the number of each job's posting on Linkedin.

When sorted by numerical information behind each type of estimates, the estimation made by the crowd is evidently better than the one made by individuals. Table V shows that compared to the mean estimate of individuals, the crowd is obviously much closer to the BLS data in most instances. In other words, the outcomes behave much better when respondents are considered as a group rather than regarded as independent individuals. More specifically, although differences still exist, the crowd estimates of minimal projected growth turn out to be negative, -60 and -0.0047 respectively, which are therefore consistent with the negative BLS data, -86460 and -0.0847 respectively, whereas the results of individuals are positive. Besides, the maximum estimation of wages and the minimum estimation of current demand are so close to BLS estimates that the former is only 7.78% less and the latter is only 1429 larger than BLS estimates. While the individuals make much worse estimates. Estimation on highest median annual wages goes far beyond the largest value of BLS data.

Table VII

Numbers of Estimates Made by Individuals the Same as BLS Estimates

Constraints	Question	Estimation of BLS data	People make the same estimation as BLS data	
			Number	Percentage
Wages	The highest median wage	family and general practitioners	6	10.00%
	The lowest median annual wage	waiters and waitresses	31	51.67%
Projected growth	The most number of new jobs	Home Health Aides and Personal Care Aides	10	16.67%
	The least number of new jobs	Retail Salespersons	0	0.00%
Projected growth	The fastest number of growing rate	Home Health Aides and Personal Care Aides	5	8.33%
	The slowest number of growing rate	Computer Hardware Engineers	4	6.67%
Current demand	The largest number of job postings	Compensation and Benefits Managers	0	0.00%
	The smallest number of job postings	Hand Laborers and Material Movers	1	1.67%
			Average:	11.88%

Exploring the final outcomes sorted by original data, we find that individuals are not able to make good estimates on predicting Hot Jobs. Table VII indicates that sorted by job titles, estimates made by individuals tend to be unwise, the possibility that one respondent can make a right estimation for each question is only 11.88%. While there remain two questions that no one makes the right estimates.

To sum up, the crowd estimation on Hot Jobs in the future is better than the individual estimation. In other words, while the members are individually biased and the crowd not particularly accurate, the crowd is still wise relative to the individual.

5.3 Which factors attribute to people's good/bad prediction on the future Hot Jobs?

Table VIII partly shows the result of simple linear regression to explore the effect of personal characteristics on the number of making the correct estimation. All variables are defined as shown in Table X.

From the table below, the following 4 conclusions can be drawn:

Table VIII

Simple Linear Regression to Explore the Effect of Personal Characteristics on the Number of Making Correct Estimation

Rightnum	Coef.	Robust Std. Err.	t	P>|t|	(95% Conf. Interval)	
Cage						
2	0.9088009	0.4053403	2.24	0.038	0.0572126	1.760389
3	1.094289	0.5067268	2.16	0.045	0.0296956	2.158883
4	1.975139	0.5687455	3.47	0.003	0.7802489	3.170029
Ccountry						
2	2.186143	0.909165	2.40	0.027	0.2760581	
conJob_years	-0.397581	0.1484744	-2.68	0.015	-0.7095141	-0.085648

Note: In this model, dependent variable is rightnum. The regression is rightnum=β_1*dgender+β_2 *i.cage+β_3 *i.ccountry+β_3 * i.cstudent+β_4 * i.dwork_experience+β_5 * conjob_took +β_6 *conjob_years+β_7 * ambitious+cons

1) Compared with people who are aged less than 20 years old, respondents aged between 21-23 years old increase the right number of estimation by 0.91, the significant level is 5%. (P< 0.05)

2) Compared with people who are aged less than 20 years old, respondents aged between 24-26 years old increase the right number of estimation by 1.09, the significant level is 5%. (P< 0.05)

3) Compared with people who are aged less than 20 years old, respondents aged between 27-29 years old increase the right number of estimation by 1.98, the significant level is 5%. (P< 0.05)

4) One additional year of job experience for people, decreases the right number of estimation by 0.4, the significant level is 5%. (P< 0.05)

In other words, age may have a positive effect on making the right estimation on Hot Jobs in the near future, while job experience has negative effect on the dependent variable.

Table IX

Logit Regression to Explore the Effect of Personal Characteristics on the Possibility of Making Correct Estimation on Jobs that Have Lowest Median Wages

Q13	Coef.	Robust Std. Err.	z	P>|t|	(95% Conf. Interval)	
Age						
2	-14.9451	1.56196	-9.57	0.000	-18.00648	-11.88371
3	-14.01869	1.78117	-7.87	0.000	-17.50972	-10.52766
student						
3	-14.11641	2.827399	-4.99	0.000	-19.65801	-8.574805
_cons	12.18302	2.927299	4.16	0.000	6.445618	17.92042

Note: In this model, the dependent variable is q13. The regression is $Pr(y=1|x_1,x_2,x_3,\ldots,x_8)=\frac{\exp(\beta_0+X_1\beta_1+X_2\beta_2+X_3\beta_3+\cdots+X_8\beta_8)}{1+\exp(\beta_0+X_1\beta_1+X_2\beta_2+X_3\beta_3+\cdots+X_8\beta_8)}$, where the dependent variable is making correct estimation on question 13, which is jobs that have lowest median wages.

The study makes a further analysis of the only correct crowd estimation: jobs that have the lowest annual median wages. Table IX is the logit model regression to verify the effect of different factors on making a right estimation of the question that which is which job has the lowest annual median wages. All variables are defined as shown in Table X.

From the table above, the following conclusions can be drawn:

1) Compared with people who are aged between 18-20 years, respondents aged between 21-23 years old have the negative effect on make right estimation on jobs that have lowest median annual wages, the significant level is 1% (P< 0.01).

2) Compared with people who are aged less than 17 years, respondents aged between 21-23 years old have the negative effect on make right estimation on jobs that have lowest median annual wages, the significant level is 1% (P< 0.01).

3) Compared with people who are bachelor students or middle school students, respondents being PhD student have the negative effect on make right estimation on jobs that have lowest median annual wages, the significantce level is 1% (P< 0.01).

The results of the linear regression model and logit model show opposite outcome of the effect of age on the number of picking right items.

The two models obtain different outcomes of impact from age. The simple regression gives that age has a positive effect on making the right estimation on Hot Jobs in the near future. The logit model gives that age has a negative effect on making the right estimation on one specific question – which jobs have lowest median annual wages. The different outcome may due to two reasons. First, the dependent variable is differing between the two models. Second, the model is quite different.

To sum up, the regression analysis shows that

1) Age may have an impact on crowds estimation on Hot Jobs refers to different models and dependent variable.
2) The years of job experience have a negative effect on the dependent variable.
3) Compared with people who are bachelor students or middle school students, respondents being PhD student have negative effect on make right estimation on jobs that have lowest median annual wages.

Table X

Description Of All Variables In The Simple Linear Regression Model And The Logit Model

	Variables	Description
Dependent Variable of simple linear regression	Rightnum	Continuous variable. The right number of making correct estimation on each questions: highest/lowest wages, largest/smallest number of new jobs, fastest/slowest growing rate, and largest/smallest number of job postings.
Dependent Variable of simple linear regression	q13	Dummy variable. Making correct estimation of question 13, which is jobs that have lowest median wages. (=1 correct, =0 wrong)
Independent Variable	Dgender	Dummy variable. (=1 male, =0 female)
	Cage	Category variable. (=0 ≤17s, =1 18s-20s, =2 21s-23s, =3 24s-26s, =4 27s-29s, =5 ≥30)
	Country	Category variable. (=0 Asia, =1 Europ, =2 North America, =3 South America, =4 Australia and Oceania, =5 Africa)
	Cstudent	Category variable. (=0 middle school, =1 bachelar, =2 master, =3 PhD, =4 Working, =5 Others)
	dwork_experience	Dummy variable. (=1 yes, =0 no)
	conjob_took	Continuous variable. Number of job taken.
	conjob_years	Continuous variable. Number of working years.
	ambitious	Continuous variable. Number of working ambition.

6. Discussion and Conclusion

In the context of numerous experimental studies of the wisdom of crowd and the direction that the crowd is wiser than single individuals in three main types of problems: cognition, coordination and cooperation problems, this research focus on exploring whether the crowd is still wise in face of a realistic complex forecasting problem: forecasting Hot Jobs in the near future. Therefore the main task of our research is different from previous lab experiments that mainly investigated simple numerical problems. Another key difference between our study and previous studies is that the discussion object, Hot Jobs, does not have a factual correct answer. We give the ambiguous phenomenon a specific definition and break it into 3 component parts. In the process of analyzing, BLS data are not only used to create a job choice list but also used to generate estimation outcomes. Therefore the survey data is not the only resource for further analysis. Furthermore, due to the decomposable concept of Hot Jobs, we find that the crowd performance can be either good or bad based on different comparison approaches. More specifically, the crowd is unwise by simply comparing job titles according to 3 constraints between the BLS estimation and the crowd estimation. However, the crowd is wise by comparing numerical information of 3 constraints between the BLS estimation and the crowd estimation.

Considering different measures, the results of the thesis suggest that when confronting with complex realistic forecasting problems, the crowd have good judgements to a certain extent.

The research demonstrates three major findings. The first finding is that by simply comparing the job titles of BLS final estimates with the crowd final estimates, the crowd performs poorly in front of a complex realistic problem. We rank top 5 most voted jobs according to the crowd estimation outcomes of eight questions and simply compare the job titles between crowd estimation results and BLS estimative results. The comparison outcome pessimistically shows that the crowd is unwise and is unable to make a good estimation on Hot Jobs in the near future.

Secondly, the crowd performs wisely when the estimate outcomes are broken down into numerical information. Although the crowd failed to estimate exactly correct jobs in terms of job titles, they are able to select jobs that are relatively quite close to the requirement of the questions analyzed via numerical information.

Thirdly, simultaneously facing a series complex problem, the crowd forecasting result is better than the individual forecasting result. We analyze the numerical information of estimations made through each individual by taking the unweighted arithmetic mean value and compare the results with most voted outcomes of the crowd. We find that the crowd voting estimation outcome is evidently better than individuals' average outcome. This leads to the conclusion that crowds can perform better than individuals on complex problems.

Fourthly, the correct estimative outcomes of the crowd can be influenced by education and age of the respondent. In addition to this, in the process of analysis of the first hypothesis, there is a fact that each of the first ranked estimative outcome of 6 out of 8 questions is made by over one-third respondents. Is there some kind of systematic biases of these incorrect choices of people? Simmons et al (2010) summarized that the systematically biased group judgement can be explained by three aspects of statements. Firstly, people are more likely to overestimate the likelihood of the outcome that they preferred. Secondly, many systematic biases exist among innocent crowds like students. Thirdly, highly motivation can also lead to systematic biases of the crowd. However, we could not find the significant correlation between latent variables like personal charactristics, and the estimative outcomes of the crowd. This may be caused by the small sample size and the setting of survey questions.

The limitation of the study can be discussed in two aspects. In the beginning, the number of participants is limited, only 59 valid responses are successfully collected. Due to the tight budget, the survey is distributed without payment. Participants may lack motivation to fulfill the whole survey, especially the last mental costly questions. Another problem is related to BLS data generation. The BLS database is run by the United States and gathers employment information only within the U.S. However, the survey is conducted in the Netherlands, and most respondents come from Asia countries. The geographical restrictions between BLS data and the crowd may bias the comparison results to some extent.

References

Bradburn, N. M., & Mason, W. M. (1964). The effect of question order on responses. Jour McFarland, S. G. (1981). Effects of question order on survey responses. Public Opinion Quarterly, 45(2), 208-215.

Bandura, A. (1977). Self-efficacy: toward a unifying theory of behavioral change. Psychological review, 84(2), 191.

Berk, Marc L., Nancy A. Mathiowetz, Edward P. Ward, & Andrew A. White. 1987. "The Effect of Prepaid and Promised Incentives: Results of a Controlled Experiment." Journal of Official Statistics 3(4):449-57.

Brown, G. (2015). Engaging the wisdom of crowds and public judgement for land use planning using public participation geographic information systems. Australian Planner, 52(3), 199-209.

Chaney, D. W. (2013) An overview of the first use of the terms cognition and behavior. Behavioral Sciences, 3(1), 143-153.

Cognition. (2018).Oxford English Dictionary. Oxford University Press. *oed.com.* Retrieved 30 July 2018, from http://www.oed.com/viewdictionaryentry/Entry/35876

Davis-Stober, C. P., Budescu, D. V., Dana, J., & Broomell, S. B. (2014). When is a crowd wise?. Decision, 1(2), 79.

Einhorn, H. J., Hogarth, R. M., & Klempner, E. (1977). Quality of group judgement. Psychological Bulletin, 84(1), 158.

Finding Hot Jobs: Using data to locate career opportunities. (2016, December) . Retrieved April, 3, 2018, https://www.bls.gov/careeroutlook/2016/article/hot-jobs.htm

Galton, F. (1907). Vox populi (The wisdom of crowds). Nature, 75(7), 450-451.

Green, C. D. (1996). Where did the word" cognitive" come from anyway?. Canadian Psychology/Psychologie canadienne, 37(1), 31.

Gigone, D., & Hastie, R. (1997). Proper analysis of the accuracy of group judgements. Psychological Bulletin, 121(1), 149.

Griffiths, T. L., & Tenenbaum, J. B. (2006). Optimal predictions in everyday cognition. Psychological science, 17(9), 767-773.

Goldstein, D. G., McAfee, R. P., & Suri, S. (2014, June). The wisdom of smaller, smarter crowds. In Proceedings of the fifteenth ACM conference on Economics and computation (pp. 471-488). ACM.

Görzen, T., & Kundisch, D. (2016, June). Can the Crowd Substitute Experts in Evaluating Creative jobs? The Case of Business Models. In ECIS (pp. Research-in).

Hogarth, R. M. (1978). A note on aggregating opinions. Organizational behavior and human performance, 21(1), 40-46.

Hong, L., & Page, S.E. (2004). Groups of diverse problem-solvers can outperform groups of high-ability problem-solvers. Proceedings of the National Academy of Sciences, 101, 16385-16389.

Hastie, R., & Kameda, T. (2005). The robust beauty of majority rules in group decisions. Psychological review, 112(2), 494.

Judge, T. A., & Bretz, R. J. (1991). The effects of work values on job choice decisions (CAHRS Working Paper# 91-23). Ithaca, NY: Cornell University, School of Industrial and Labor Relations. Center for Advanced Human Resource Studies, 1-35.

Judge, T. A., & Bretz, R. D. (1992). Effects of work values on job choice decisions. Journal of applied psychology, 77(3), 261.

Knight, & Hazel (1921), “Reliability of Judgements: A Comparison of Group and Individual,” Master’s thesis, Columbia University.

Klugman, S. F. (1945). Group judgements for familiar and unfamiliar materials. The Journal of General Psychology, 32(1), 103-110.

Koriat, A. (2008). Subjective confidence in one's answers: the consensuality principle. Journal of Experimental Psychology: Learning, Memory, and Cognition, 34(4), 945.

Lorge, I., Fox, D., Davitz, J., & Brenner, M. (1958). A survey of studies contrasting the quality of group performance and individual performance, 1920-1957. Psychological bulletin, 55(6), 337.

Lusk, E. J., & Oliver, B. L. (1974). American managers' personal value systems—revisited. Academy of Management Journal, 17(3), 549-554.

Lorenz, J., Rauhut, H., Schweitzer, F., & Helbing, D. (2011). How social influence can undermine the wisdom of crowd effect. Proceedings of the National Academy of Sciences, 108(22), 9020-9025.

Lyon, A., & Pacuit, E. (2013). The wisdom of crowds: Methods of human judgement aggregation. In Handbook of human computation (pp. 599-614). Springer, New York, NY.

Laughlin, P. R. (2014). Group decision making and collective induction. In Understanding group behavior (pp. 69-88). Psychology Press.

Mozer, M. C., Pashler, H., & Homaei, H. (2008). Optimal predictions in everyday cognition: The wisdom of individuals or crowds?. Cognitive Science, 32(7), 1133-1147.

Mannes, A. E. (2009). Are we wise about the wisdom of crowds? The use of group judgements in belief revision. Management Science, 55(8), 1267-1279.

Mannes, A. E., Larrick, R. P., & Soll, J. B. (2012). The social psychology of the wisdom of crowds.

Muchnik, L., Aral, S., & Taylor, S. J. (2013). Social influence bias: A randomized experiment. Science, 341(6146), 647-651.

Mannes, A. E., Soll, J. B., & Larrick, R. P. (2014). The wisdom of select crowds. Journal of personality and social psychology, 107(2), 276.

Mollick, E., & R. Nanda (2015). "Wisdom or Madness? Comparing Crowds with Expert Evaluation in Funding the Arts." Management Science (Article in advance), 1-21.

Rubinstein, A., & Salant, Y. (2006). A model of choice from lists. Theoretical Economics, 1(1), 3-17.

Surowiecki, J. (2004). The wisdom of crowds: Why the many are smarter than the few and how collective wisdom shapes business. Economies, Societies and Nations, 296.

Simmons, J. P., Nelson, L. D., Galak, J., & Frederick, S. (2010). Intuitive biases in choice versus estimation: Implications for the wisdom of crowds. Journal of Consumer Research, 38(1), 1-15.

Treynor, J. L. (1987). Market efficiency and the bean jar experiment. Financial Analysts Journal, 43(3), 50-53.

The Top 20 Valuable Facebook Statistics. (2018, July 9). Retrieved July, 15, 2018, from: https://zephoria.com/top-15-valuable-facebook-statistics/

Taylor, K. M., & Betz, N. E. (1983). Applications of self-efficacy theory to the understanding and treatment of career indecision. Journal of vocational behavior, 22(1), 63-81.

Vul, E., & Pashler, H. (2008). Measuring the crowd within: Probabilistic representations within individuals. Psychological Science, 19(7), 645-647.

8. Appendix

Table XI

Hot Job Estimation of the Crowd and Estimation of Real World Data Sorted by Occupations

Constraints	Question	Estimation of the crowd	Estimation of real world data
Wages	The highest median wage	Management Occupations	Healthcare Practitioners and Technical Occupations
	The lowest median annual wage	Food Preparation and Serving Related Occupation	Food Preparation and Serving Related Occupations
Projected growth	The most number of new jobs	Architecture and Engineering Occupations	Healthcare Support Occupations
	The least number of new jobs	Legal Occupations	Sales and Related Occupations
Projected growth	The fastest number of growing rate	Computer and Information Research Scientists	Healthcare Support Occupations
	The slowest number of growing rate	Life, Physical, and Social Science Occupations	Architecture and Engineering Occupations
Current demand	The largest number of job postings	Food Preparation and Serving Related Occupations	Management Occupations
	The smallest number of job postings	Life, Physical, and Social Science Occupations	Transportation and Material Moving Occupations

Table XI shows the final estimation sorted by occupation[4]. The conclusion made by previous table stays consistent. In a more general concept of jobs, estimates made by the crowd remain quite different from BLS estimates except for the only correct one.

[4] Occupation: is a more general concept of job.