What Do Jobseekers Want?

Comparing Methods to Estimate Reservation Wages and the Value of Job Attributes

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August 2022

Abstract

Understanding jobseeker preferences—including their reservation wages and how much they value different non-wage amenities—is difficult because they are not directly observable. We test four different methods for estimating these preference parameters using an experiment in a job-matching center. We find large and important differences between the methods. Using a follow up survey for validation and comparing the consistency of estimates with prior literature we find that Discrete Choice Experiments perform best. We show how these methods can improve our understanding of labor market frictions and help policymakers and employers develop targeted policies and compensation bundles to address inequities in the labor market.

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The authors would like to thank Rahma Ali, Norhan Muhab and Eslam Serrag for research assistance. Thanks also to the staff at the National Employment Pact including Rasha Badran, Mohamed Ezzat and Eman Mohammed for excellent implementation support, and many thanks to the participants in our study. We benefited from helpful comments from 3 referees and the editor, Alex Bartik, Andrew Garin, Kareem Haggag and Jamin Speer as well as participants at the ERF 26th Conference and Innovation for Poverty Action's Methods & Measurement Conference. UIUC IRB approval #18671, AEA Registry # 9957. This project was possible thanks to funding from The Univeristy of Illinois' RIFDC. Authors retained full intellectual freedom throughout the entirety of the project, all errors are our own.

1 Introduction

Many developing country labor markets are characterized by high levels of unemployment. Understanding exactly why this is true is complicated by a lack of high quality data on labor market conditions in these contexts. Matching frictions are recognized as a primary market failure that contributes to unemployment (Banerjee & Sequeira, 2022; Kelley, Ksoll, & Magruder, 2021; Abebe et al., 2020), and central to understanding these frictions are job seeker beliefs (Dal Bó, Finan, & Rossi, 2013; Krueger & Mueller, 2016), which can have both short and long term impacts on their careers (Bandiera et al., 2021). Knowing people's reservation wages and the value placed on different job amenities could help improve our understanding of how the labor market functions. However, these values are not directly observable, leading researchers to attempt to measure these parameters using a variety of methods. But different methods could yield different estimates, which in turn could change conclusions about optimal policy.

Empirical efforts to measure jobseekers' reservation wages and valuation of other work attributes often use indirect methods (i.e. revealed preferences, as in Rosen, 1986; Stern, 2004 and Lavetti and Schmutte, 2018) which require strong assumptions, or one of a number of direct methods (i.e. stated preferences as in Eriksson and Kristensen, 2014 and Wiswall and Zafar, 2017). Direct questions usually focus primarily on the monetary reservation wage, by using questions that ask people to report what they believe their reservation wage is (e.g. Krueger and Mueller, 2016; Caliendo, Lee, and Mahlstedt, 2017). But many jobseekers struggle with precisely articulating their own reservation wages. For example, we suggest that the reader attempt to think about their answer to one of the most common questions used to measure reservation wages: "What is the minimum salary you would be willing to accept for a job?". A common response is "it depends".

We implement a survey experiment inside a job matching center in Cairo, Egypt to assess how different direct response methods compare to each other when estimating reservation wages and the valuation of job attributes. As job seekers signed up for matching support, they were asked to fill out a form that randomized the method used to collect their reservation wage and valuations of job attributes. We consider 4 different strategies commonly used in the literature: (1) Open Ended Questions, (2) Payment-Card Questions, (3) Double Bound Dichotomous Choice Questions, and (4) Discrete Choice Experiments. “Open Ended” questions simply ask individuals to report the minimum value they would accept for a given job. “Payment-Card” questions provide multiple choices that people can pick from. “Double Bound” questions ask two binary questions - would you accept this job if it paid “X”, and then bounds their valuation by asking a second question: “would you accept this job if it paid “X+Y” if they said no, or “X-Y” if they said yes. Discrete choice experiments provide two job offers and ask the individual to choose one of the jobs, or to refuse both jobs. It does this many times- in our experiment individuals were presented 15 pairwise comparisons.

We find that valuations are sensitive to the method used to measure them.[1] Estimated reservation wages, conditional on a constant job attribute bundle, vary widely. Job seekers in our sample were primarily interested in blue-collar jobs. We find that their reservation wages range from a low of 1,831 Egyptian Pounds (EGP) a month using discrete choice experiments (minimum wage in Egypt is 1,200 EGP/month, 1USD$\simeq$16EGP) to 2,515EGP/month using open ended questions, a 37% difference. The payment card method estimates a monthly reservation wage of 2,238EGP and the double bound estimates it to be 2,045. All 4 of these estimates are economically and statistically significantly different from each other. Furthermore, the estimated reservation wages are not highly correlated across methods, with correlation coefficients of 0.21 or below. We also consider how these methods perform in estimating the value of specific job amenities. We find that certain methods produce estimates that are more precise and more consistent with our understanding of the labor market than others. For example our estimates using open-ended method, if taken at face value, imply that employers would need to pay their employees *more* if the employers provide free meals on the job. This contrasts sharply with estimates from the discrete choice experiments which value free meals in line with what the value of those meals cost in this context.

In the past inconsistencies like these have led researchers to consider stated-preference approaches as inadequate for valuing market and non-market goods (Diamond & Hausman,

[1] The psychology and survey design literature discuss why different options could lead to different answers (Tourangeau, Rips, & Rasinski, 2000; Rossi, Wright, & Anderson, 2013). This includes anchoring bias (Rowe, Schulze, & Breffle, 1996), social desirability bias (Krumpal, 2013), and cognitive uncertainty amongst others (Enke & Graeber, 2021a, 2021b).

1994). We contend that the problem is in the particular type of stated-preference approach and not stated-preference approaches in general. In particular, the discrete choice experiment method provides estimates that are all in line with our understanding of the labor market and market prices, while only taking 40 seconds longer to implement on average relative to the other elicitation methods.

To further assess accuracy across methods we implement a follow up survey with respondents about 2 years after the initial randomization. We collect data on existing employment, compensation and amenities offered at their job. We find that the discrete choice experiment provides estimates most consistent with economic theory. We also estimate a reservation wage residual as a proxy for how "choosy" an individual is and compare it to the likelihood an individual was employed at the follow up survey. We find that all methods struggle to predict long term unemployment.

Finally, we utilize the data from the discrete choice experiment to describe how valuation of job attributes differ by gender. We find that men and women value job attributes differently. Women are much more sensitive to long commutes, requiring compensating differentials that are twice as large as men for commuting 60 minutes to work relative to a baseline commute of 30 minutes (similar to what is found in Le Barbanchon, Rathelot, and Roulet, 2020). We also provide suggestive evidence that men value health insurance more than women, while women value daycare options at work more than men.

We make three main contributions. First, we contribute to the literature that studies how individuals set their reservation wages (e.g. Caliendo, Tatsiramos, and Uhlendorff, 2013; Krueger and Mueller, 2016; DellaVigna, Lindner, Reizer, and Schmieder, 2017). Due to a lack of data, these studies often use responses to "open ended" questions, or revealed preference measures that need to make strong assumptions about outside options. We show that open ended questions produce results that are noisy and inconsistent with local estimates of the value of certain amenities. This is crucial since many recent studies that analyze how reservation wages are affected by the design of unemployment insurance benefits and the length of unemployment rely on this elicitation method (e.g. Krueger and Mueller, 2016; Koenig, Manning, and Petrongolo, 2016; Le Barbanchon, Rathelot, and Roulet, 2019). On the other hand, our discrete choice experiments (which researchers have started to utilize more recently) perform best while taking less than a minute longer to administer.

Second, we contribute to the literature that attempts to value different work amenities. Previous work has looked at the value of schedule and location flexibility (e.g. Wiswall and Zafar, 2017; Mas and Pallais, 2017; He, Neumark, and Weng, 2021; Chen, Ding, List, and Mogstad, 2020), as well as as certain types of fringe benefits (Eriksson and Kristensen, 2014; Maestas, Mullen, Powell, Von Wachter, and Wenger, 2018). We contribute to this literature by including additional amenities like free daycare and considering the importance of commute time (Le Barbanchon et al., 2020). Moreover, while the vast majority of studies focus on how individuals from developed countries value job amenities, there is less research focused on developing countries[2]. Showcasing that preferences for job amenities can differ by local context is important for understanding why labor markets may reach different equilibria in different places with respect to issues like female labor force participation and gender wage gaps. We also provide greater external validity relative to earlier studies by utilizing a sample of current jobseekers instead of students or people who are not actively looking for work.

Third, by comparing estimates resulting from several different elicitation methods our paper makes a contribution to improving measurement and to the field of survey design (Diamond and Hausman, 1994; Tourangeau et al., 2000), in particular regarding the valuation of amenities using stated preference methods (Bateman et al., 2002). The amenities over which we find differences in willingness to pay across elicitation methods are both market and non-market goods. This contrasts with previous studies that focus on non-market or public goods (e.g. Brown, Champ, Bishop, and McCollum, 1996; Welsh and Poe, 1998; Hanley, Wright, and Adamowicz, 1998; Cameron, Poe, Ethier, and Schulze, 2002). The fact that some of the amenities we include can be purchased in the market should reduce the likelihood that different elicitation methods would yield different willingness to pay estimates for these attributes. Despite this, we still find large differences across elicitation methods suggesting that results obtained from certain stated preference methods should be taken with caution.

[2]A notable exception is He et al., 2021, who study preferences for flexible jobs among white collar workers in China.

2 Data and Elicitation Methods

We collected data about job seekers' preferences in collaboration with the National Employment Pact (NEP), an NGO based in Cairo that provides job matching services through their partnership with over 700 employers in Egypt. Approximately 95% of the employment opportunities that NEP offers are for blue-collar jobs.[3] Jobs advertised through NEP are required to provide social and medical insurance and to pay above the minimum wage.

NEP advertises their (free) services widely and job seekers can simply walk into one of their job matching centers to apply for support. Job seekers register with the NGO and sit with an employment officer who learns more about the candidate. Afterwards they are encouraged to fill out a supplemental survey we designed so that NEP could learn more about their job preferences. The survey included a few questions for the job seeker about their job search activities, and a series of hypothetical questions that would allow us to infer the value they place on five different characteristics of a job: travel time to the workplace, health insurance, whether the job requires working some weekends each month, and whether the job provides meals and/or daycare on-site.[4] We chose these characteristics based on the type of employment opportunities that NEP usually offers to job seekers (such as health insurance) and on suggestions from NEP's staff about what amenities they thought job seekers would care about.[5] We fielded our survey between August 2018 and March 2019. During this time 1,996 job seekers filled out our survey.

Panel A of Appendix Table A2 shows summary statistics for our sample. These jobseekers are relatively young, predominantly male and single. The average job seeker has completed high school and has been looking for a job for 8 months by the time they register with NEP. Job seekers spend approximately 15 hours a week looking for a job, almost 50% of the individuals surveyed use only one method to look for a job.

We compare our sample to a representative sample of all unemployed people in Egypt using the 2017 Harmonized Labor Force Survey (HLFS, OAMDI, 2019). Our sample is

[3]According to the 2017 Harmonized Labor Force Survey, almost 50% of wage employees in Egypt are blue-collar workers.

[4]In Appendix Table A1 we show the values that each of these attributes could take.

[5]Despite NEP requiring employers to offer health insurance in order for them to advertise the jobs, most employers in Egypt do not provide health insurance to their workers.

slightly older, while years of education and marriage rates are similar across samples. Our survey respondents have been looking for a job for a shorter period of time than unemployed individuals in the HLFS.

2.1 Elicitation Methods and Estimation Strategies

To assess the sensitivity of reservation wages to the elicitation method used, we randomized respondents into three different groups. The first group was shown "open ended" questions, the second group was given "payment card" questions,[6] and the third group got a set of "double-bound dichotomous choice" questions. Appendix Table A3 includes a balance test across randomized groups and shows that the groups are statistically equivalent.

In each method, we describe a job with a specific bundle of attributes, and ask the jobseeker what was the lowest wage or salary they would accept for that job. For each person we did this many times, with each respondent considering 7 separate bundles. Importantly, the bundles were kept constant among the three methods, and so every person in the sample considered the same 7 job bundles. The difference across these 3 methods are not in the questions that were asked, but in the way participants were able to respond. Appendix Table A4 lists the questions that participants were asked using these three methods.

The 7 separate questions differed in the attributes of the job. These attributes included the commute time to the job (in minutes), whether it included healthcare for the respondent and their spouse, whether it required the person to work certain weekend days, and whether meals or daycare were included benefits of the job.

The response options across the three methods differed in the following ways: in the "open ended" questions, individuals were able to respond with any value they wanted. In the "payment card" method, individuals would pick a value from a multiple-choice list. In the "double-bound" method, individuals would be asked if they would accept the job at a pre-determined wage, and then depending on their response would be asked a second question that was higher (if they said no to the first question) or lower (if they said yes).

After individuals reported their valuations for the 7 job bundles, all 3 groups were then

[6] The "payment card" question is equivalent to a "multiple-choice" question, but there is a long history in the literature of referring to it by that name, which we follow here (Mitchell & Carson, 1981).

asked to go through the discrete choice experiment. This differs from the direct questions because individuals now would consider two different job bundles (including a wage for the bundle) and asked to choose between them (or choose to decline both jobs). Individuals were asked to make this choice across 15 different job pairs. Below, we describe each method used in more detail, including their strengths and drawbacks.

2.1.1 Open-ended Questions

Open-ended questions are the most common type of elicitation method used in labor force surveys (see for example Faberman, Mueller, Şahin, and Topa, 2017; Krueger and Mueller, 2016 and Hall and Mueller, 2018). They amount to directly asking an individual what is the minimum wage required for them to take a job with the associated attributes. The answer is typically considered to be the reservation wage of the person. Figure A1 provides an example of the type of questions respondents faced.

The main benefit of this method is that it avoids any bias that may stem from showing the individual one or more values they can pick from. Moreover, because each response is a single value rather than an interval, it is straightforward to estimate the value placed on each of the job attributes.

The main drawback of this elicitation method is that because individuals are allowed to input any value, estimates can be sensitive to the presence of outliers. These questions also do not reflect a situation that job seekers typically encounter when receiving a job offer, so even though the questions may seem simple, respondents may have difficulty in coming up with reasonable answers. For example. 98% of the answers are multiples of 100 despite individuals being able to give any integer amount as an answer.

2.1.2 Payment Card

Instead of allowing individuals to choose any wage as the minimum they would be willing to accept, the payment card method (Mitchell and Carson, 1981) presents a series of values for respondents to choose from, in other contexts this would normally be referred to as a "multiple choice" question. Individuals are expected to pick the lowest value that is higher than their true reservation wage (e.g. if the card shows values from EGP 1000 to EGP 2000 in intervals of 200, and a person's reservation wage for the described job offer is 1500, they should choose EGP 1600 as their answer). Figure A2 provides an example of the questions asked in the survey. The values shown lie within the 10^{th} and 75^{th} percentile of the monthly wage distribution for blue-collar workers, according to the 2017 HLFS.

By bounding the possible choices of the respondent, the payment card format is not affected by outliers. However, there is evidence that responses can suffer from anchoring bias: the response given by an individual may be affected by the range of values shown, even if their reservation wage is contained within the ranges shown (Rowe et al., 1996). We explore this further through auxiliary experiments outlined in section 2.1.5 below. Providing a set of options also may induce social desirability bias, where the respondent attempts to intuit what the surveyor wants to hear and answers in line with that belief instead of with the true value for the respondent themselves (Krumpal, 2013).

2.1.3 Double-bound Dichotomous Choice

The dichotomous choice method (also known as the "referendum method") has been one of the most popular contingent valuation methods used by researchers to value non-market goods (see for example Hanemann, Loomis, and Kanninen, 1991 and Carson et al., 2003). This method presents the same job bundle and then asks whether the respondent would take the job for a given salary. We randomized the starting salary at the respondent level to be between EGP 1000 and EGP 2400 in EGP 200 increments to minimize starting point bias (Herriges & Shogren, 1996). As with the values for the payment card format, these values lie within the 10^{th} and 75^{th} percentile of the monthly wage distribution for blue-collar workers, according to the 2017 HLFS. Figure A3 shows an example of a question under this elicitation format.

In its most basic form, this is simply a series of take-it-or-leave-it offers (one for each job described), similar to what job seekers usually face in the labor market. However, these questions convey little information: a "yes" only means that the respondent's reservation wage for the job is between 0 and the proposed amount, and a "no" that the reservation wage is bounded between that amount and infinity. For this reason, we adopted a double-bound version of this method, which consists of asking an additional question for each hypothetical job offer: if the respondent accepted (rejected) the first offer, the second question lowers (raises) the salary offered. While in most studies the price of the follow-up offer is a fixed fraction of the first offer, we randomized the amount of the follow-up offer to be between EGP 150 and EGP 500 to further test sensitivity of the responses to the available options (which we discuss further in Section 2.1.5 below).

If the individual answers "Yes" to the first question, and "No" to the second, we know that their reservation wage for the proposed job lies between the second and the first values shown. Similarly, if the answers are "No" and "Yes" respectively, the person's reservation wage would lie between the first and second bids. If the individual replies "No" to both questions, we can bound their reservation wage from below by the second amount offered, while if they answered "Yes" to both questions, we can bound their reservation wage between 0 and the second offered wage.

2.1.4 Discrete Choice Experiment

Discrete choice experiments (DCE) have been widely used in transportation and health economics (Greene and Hensher, 2003, Adamowicz, Louviere, and Williams, 1994), and in recent years labor economists began using them as an alternative to revealed preference methods employed to estimate compensating wage differentials (Mas and Pallais, 2017; Wiswall and Zafar, 2017). Their main advantage is that they resemble how individuals maximize their utility in their everyday life, and how valuation of the attributes of interest would be carried out in a revealed preference framework. Many attributes can be varied at a time while keeping the task tractable for respondents.

In our choice experiment, individuals were separately randomized into one of 10 blocks of 15 choice sets. These choice sets contain two job offers each, which vary in one or more of the five characteristics mentioned before as well as their salary.[7] For each choice set, individuals are asked to pick their most preferred alternative, or no offer at all if they would reject both job offers. An example is presented in Figure A4.

[7]Because our fictitious jobs contain six attributes with between two and four values each, there are 384 possible jobs. A full factorial design would give over 70,000 job combinations for job seekers to choose from. Instead, we used the "JMP Statistical Discovery" package from SAS to create a fractional factorial design with the properties of orthogonality and level balance, which enables us to estimate the main effects parsimoniously.

2.1.5 Testing for Consistency *within* Elicitation Method

In addition to comparing different elicitation methods to each other we cross randomized within elicitation methods as an additional test of the sensitivity of estimates to elicitation parameters. We implemented three associated auxiliary experiments. While our main experiment allows us to compare the sensitivity of responses *across* elicitation methods, these experiments allow us to assess the sensitivity of responses *within* elicitation method.

First, in the open ended, pay-card and double-bound methods a random half of participants had their first question describe a job that included health insurance, while the other half had their first question describe a job that did not include health insurance.

Second, for the payment card method we also randomized the range of values shown to people. Respondents were given one of two lists of responses, the first varied from 1000 to EGP 2200 and the other ranged from EGP 1400 to EGP 2600, in both cases with EGP 200 increments.

Third, in the double-bound dichotomous choice individuals are asked if they would accept a job at a given wage ("X") and then asked a follow up question that add or subtracts a second value to bound their valuation ("X +/- Y"). We randomized individuals into 5 different values of "Y", to test the sensitivity of responses to interval size.

We control for these auxiliary experiments in our main experiment specifications and describe their impacts in section 3.4 below.

3 Comparing Estimation Methods

We estimate reservations wages and the valuation of job attributes using a set of straight forward regressions. The primary specification takes the following form:

$$W = \sum_{k\in\{60,90,120\}} \beta_k \times Commute_k + \sum_{d\in\{S,SP\}} \lambda_d \times Hins_d + \gamma Weekend + \mu Meals + \theta Daycare + \varepsilon$$

Where W is the wage chosen by the respondent and each covariate represents a dummy for whether the attribute was provided by the job in the hypothetical question they were asked. There were four different levels of commutes (30, 60, 90 and 120 minutes from home), and three different levels of health insurance (no insurance, only for self, for self and spouse).[8]

For the open ended questions this is estimated utilizing a classic OLS regression. The payment card method only gives us a bound within which the actual reservation wage for each hypothetical job lies, so we use an interval data model that we estimate via maximum likelihood (Cameron and Trivedi, 2005). In this case, besides the covariates for each job characteristic we include a dummy for the range of values in the payment card that individuals observe. For the double-bound dichotomous choice procedure we also utilize the same type of maximum likelihood estimation.

Finally for the discrete choice experiment we use respondent's choices to estimate their willingness to pay for each attribute using a mixed logit model (Revelt and Train, 1998, McFadden and Train, 2000). The use of this specification is possible since we observe multiple choices made by each respondent, which allows the parameters of interest to vary randomly across respondents.[9] This permits us to obtain estimates of the parameters of interest for each individual as well as means for the entire sample. Moreover, the model does not require one to assume independence of irrelevant alternatives (IIA), which is unlikely to hold in a setting like this where jobs can vary in many dimensions.

3.1 Reservation Wages

We begin by comparing estimated reservation wages for the most basic job that participants are presented with. This job requires a 30-minute commute, does not provide health insurance, does not require working on the weekend, nor does it provide free meals or daycare at

[8]We also include controls the treatments associated with the auxiliary experiments described above when appropriate.

[9]For this estimation we produce a dataset where each job pair produces three observations, one for "job A" and its characteristics, one for "job B" and its characteristics, and one for turning them both down, where we set the value of the amenities to 0. There is then a "choice" variable that is equal to 1 if the respondent chose that option. The estimation procedure then estimates the value of each amenity in inducing the individual to choose it, while including a fixed effect for the job pair. This procedure may underestimate the reservation wage because the true outside value of turning down both jobs is the amount of money they get from family which we do not know. At the same time, when considering the other elicitation methods, the job seeker may still get money from their family if they took the other job offered to them, and we cannot control for that in the analysis either.

the workplace.[10] Table 1 reports our estimates from each of the four methods used to elicit reservation wages. Column 1 reports that the open ended questions lead to a reservation wage of 2515EGP a month, with a standard error of 38. As discussed above, the open ended format is particularly susceptible to outliers (Carson and Hanemann, 2005) and so we winsorize the values at the top and bottom 1%. Appendix Table A5 shows how the results differ by the level of winsorization. Columns 2 and 3 include the estimates from the payment card method (2238) and the double bound dichotomous choice method (2045). Column 5 includes the estimate from the discrete choice experiment.

Panel B reports the p-values for each pair-wise comparison of the average reservation wage estimated using each of the four methods tested in our experiment. It shows that each of the estimated reservation wages are statistically different from each other with all p-values<0.01.

The results in Table 1 showcase that there are large economically and statistically significant differences in reservation wages depending on the method used to estimate them. In Figure 1 we plot the reservation wages estimated from the DCE compared to the reservation wages estimated from each of the three other methods. The figure shows that these are not simply differences in levels: the correlation of reservation wages within person estimated with the DCE and each of the alternative elicitation method is low, between 0.14-0.21.

Overall, these results suggests that researchers should carefully consider how the method used to collect reservation wage data could impact their results and analysis. But which of these methods provide the estimates closest to the truth? The next section utilizes estimates from valuing job attributes to make the case that discrete choice experiments provide estimates that are most consistent with reality.

3.2 Valuing Job Amenities

We estimate the value that jobseekers place on different job amenities in Table 2. Column 1 presents the estimates from the open ended questions. Because individuals can freely choose any number as a response to each question, this method is very sensitive to outliers. Hence,

[10]The distance to work corresponds approximately to the distance to work for the average worker, according to the 2018 Egyptian Labor Market Panel Study (ELMPS).

we present the results after winsorizing responses at the top and bottom 1%.[11] This method estimates that individuals would need to be paid approximately 183 pounds more per month to accept a job that is a 60 minute commute from home, relative to one that is a 30 minute commute from home. This increases to an additional 273EGP and 408EGP a month for a job that is 90 and 120 minutes from home, respectively. We find that individuals would be willing to accept a job that pays 127EGP less if that job also offers health insurance, while needing an additional 325EGP to work on Friday, the first day of the weekend in Egypt. On the other hand we find that free meals and child care are valued as *disamenities*.

Column 2 reports the estimates when using the payment card method. These estimates are much more precisely estimated, but this is primarily due to the restrictive nature of the allowable responses. By limiting answers to a small set of choices, this method minimizes outliers and removes some of the natural variation that comes from continuous variables. While smaller standard errors are often attractive, in this case there are several instances where estimates are not logically consistent. For example, commuting 90 minutes requires a larger compensating differential than commuting 120 minutes and the value of health insurance for 1 person is larger than for 2 people. These estimates are not only at odds with the theory of compensating differentials, but also with recent empirical findings (Le Barbanchon et al., 2020). This method also estimates a value for daycare that is near zero. While this is certainly plausible, recent work has shown that daycare services are seen as valuable in this context (Caria et al., 2022).

Column 3 presents estimates using the double-bound dichotomous choice format. This method has fewer inconsistencies relative to the other methods, with the only two surprises being that there is almost no value placed on meals at the workplace and that free daycare is seen as a disamenity, with estimates suggesting that individuals would need to be paid 59EGP more to take a job that provides that service. This isn't necessarily incorrect, and we discuss this issue further in section 5 below.

Column 4 provide the estimates from the Discrete Choice Experiment (DCE) elicitation. As described above, we implemented the DCE on the full sample, as we hypothesized that

[11] In Appendix Table A5 we present the results of winsorizing responses at the top and bottom 2% and 5% levels as well, showing that estimates are robust to these changes.

this method would be the most accurate. To make the comparison of the DCE estimates comparable to the other methods, we also drew over 287 random subsamples of one third of the whole sample.[12] This makes the precision of the estimates easier to compare since the standard errors are estimated with about the same number of observations. In Column 5 we report the median estimate and standard deviation for the willingness to pay for each job attribute obtained through this exercise.[13]

We find that the DCE provides estimates with standard errors that are close to those of the double bound method. At the same time the estimates are the most consistent with earlier work and our understanding of the labor market. Compensating differentials increase with commute time, the value of health insurance increases when it covers spouses in addition to the employee, and free meals are seen as a valuable amenity that make people want the job more, as is free daycare. Overall, the results from Table 2 suggest that the DCE method provides estimates that are most accurate relative to all other methods.

3.3 Validation with Follow Up Data

We complement the experimental analysis with data obtained during a follow-up survey that was carried out in December 2020 (between 1.5 and 2 years after the baseline survey). In this survey, we asked individuals who had found a job since the baseline about its characteristics. We were able to survey 986 individuals (50% of our original sample).[14] Thankfully Table A6 shows that attrition is not correlated with the elicitation method assigned at baseline. Moreover, Table A7 shows that the determinants of attrition are quite similar across elicitation methods, even though men and married individuals were in general more likely to be found at follow-up, but this doesn't differ by treatment assignment. Of the individuals resurveyed, 891 had worked since the time they completed the baseline survey.

[12]This estimation is computationally intensive. We completed 287 estimations over the course of 3 months utilizing several computers.

[13]In addition, we present the distribution of the estimates obtained for each job attribute in Figure A5 & A6.

[14]In addition to the difficulties raised by the coronavirus pandemic to track individuals, it is common for people in Egypt to change phone numbers. It is also possible that the pandemic changed people's valuation of job attributes which would attenuate our estimates related to how their longer-term job outcomes are related to their earlier job valuations.

Job Amenities

We use the follow up data in an updated regression. We re-estimate the valuations for job attributes using the responses we obtained in the first survey, but this time we include interactions between each job characteristic and a binary variable that takes the value 1 if their most recent job contained that amenity. We contend that if the method produced accurate estimates, these interactions should be either negative or null. The intuition is based on the fact that individuals select into jobs that are better for them and avoid jobs that have attributes they don't like. This would imply that individuals that value childcare will be more likely to be in jobs that provide childcare. Hence, we should expect that an interaction between the childcare attribute and an indicator for having a job with childcare would be negative (since they value it more, and so they would accept a lower wage for that job, i.e. the coefficient would be negative). Similarly, because people avoid jobs with attributes they don't like, if they are in a job with a "negative" attribute, we expect them to dislike it less than people who completely avoid a job with that disamenity. This would imply that they "value it more", which again would lead to a negative point estimate.

Table 3 presents the results of this analysis. Column 1 show once again that using open-ended questions produces inconsistent estimates for some attributes: individuals whose job includes health insurance were willing to pay *less* for this amenity at baseline than those whose job does not include health insurance.

Column 2 presents the estimates from the Payment Card format, showing no significant differences in WTP by presence of each attribute in the current/most recent job except for health insurance. However, the inconsistencies regarding compensation for longer commutes in the main effects persist. Similarly, estimates obtained using the Double Bound Dichotomous Choice format (column 3) show no statistically significant differences for the interaction terms with the exception of the need to work on weekends, where the point estimate is positive and marginally significant.

Finally, estimates using the DCE method show the expected results: estimates for the main effects have signs consistent with the idea that individuals will require a compensation for a disamenity and would be willing to forgo part of their wage in exchange for a job amenity. Interaction terms are either negatively signed or statistically indistinguishable from zero. The only exception is health insurance for the worker and their spouse, which estimate is positive but only marginally significant (with a p-value of 0.096).

The fact that the DCE results are the only method that provide estimates on all of the job attributes in line with basic economic theory leads us to prefer the DCE method over the others for their accuracy. This is in line with our prior expectations, since discrete choice experiments mimic real world decisions better than the other methods.

Reservation Wages

We also use the follow up data to assess how well the different methods perform in estimating reservation wages. We regress the originally estimated reservation wages on baseline demographic characteristics including gender, age, education and prior work status. We take the residual of this regression and characterize individuals with a higher residual as "choosy," i.e. these are people whose reservation wages are higher than we would expect given their characteristics. We then test if those who have high residuals are less likely to have found a suitable job in the time between baseline and our follow up survey.

Figure 2 shows how each method performs on this test. We split individuals into deciles based on the residual in the regression, and then plot the proportion of individuals in each decile who are currently working or have worked at all during the follow up period. We expected the pattern to be downward sloping, with higher deciles having lower work propensities. Across all four methods the relationships between working and the residual are relatively flat. We interpret this as evidence that all methods struggle to predict who will be unemployed in the longer term.

3.4 (In)Consistency *within* Elicitation Methods

In addition to comparing the estimates across elicitation methods we implemented a few small experiments that allow us to test for consistency *within* an elicitation method. These experiments allow us to test whether responses depend on the order the questions are presented to the respondents as well as if the range of values provided in the pay-card and double-bound methods affect valuation estimates.[15]

In the first auxiliary experiment, some individuals were assigned a first job offer that does not include health insurance, and the second and third offers added this amenity for themselves and their spouses, respectively. Another group of respondents faced a first job offer that included health insurance for themselves and their spouse, and the following two offers progressively removed the number of people covered by this amenity. No other job characteristic of the pool that we tested was included in these offers.

We use the responses to test whether the order in which amenities appear influence the value given to them. To do this, in each model we include a dummy that takes the value 1 for individuals assigned to the offers that start with health insurance for themselves and their spouse and progressively removes coverage, and an interaction between this "treatment" variable and each type of health insurance coverage.

The results are shown in Table 4. To increase power, we pooled together the answers from the open-ended, payment card and double-bound dichotomous choice. Since each method yields a different type of answer (a stated figure or an interval), we use three alternative ways to estimate the parameters of interest. In column 1, we treat all the responses as intervals (in the case of open-ended question, the lower and upper bound are the same value, which correspond to the answer given by the respondent) and estimate the WTP via maximum likelihood. In column 2, we instead estimate the parameters by OLS, using the chosen value in the payment card and double-bound dichotomous choice as the respondents' reservation wage.[16] In column 3 we also use OLS but we take the midpoint of answers for the payment card and double-bound dichotomous choice methods.

We report the estimated value of health insurance as well as an interaction effect for those whose first question described a job with health insurance. We see that the interaction effect for health insurance with the spouse is always statistically different from zero, which indicates that the sequencing of the questions matters. The negative coefficient indicates that individuals value health insurance more when they "lose" this benefit, consistent with

[15]These comparisons focus on the first three methods but do not include the discrete choice experiments, making this somewhat one-sided.

[16]In the case of the double-bound dichotmous choice, we take the lowest value accepted by the respondent or the highest value shown if no offer was accepted.

loss aversion. This implies that, for example, our earlier estimates of the value of childcare conflates two things, the value of adding childcare to the job and the value of removing meals from the job. This likely leads to us underestimating the value of childcare, and potentially overestimating the value of meals (since before that question they are told about a job where they need to work weekends, and so they "lose" a negative attribute).

In the second auxiliary experiment we vary the range of options individuals are provided in the payment card and double bound methods. For the payment card method some individuals were shown "low" values (EGP 1000 to EGP 2200 in EGP 200 intervals) and others where shown "high" values (EGP 1400 to EGP 2600 in EGP 200 intervals). Appendix Table A8 presents estimates for the payment card format including interaction terms between each attribute and an indicator for being shown the "low values". Those shown a card with lower values tend to have an average reservation wage EGP 250/270 lower than those shown the card with higher values, this implies that about 65% of the randomly assigned shift in values makes it through to their valuations. In addition, respondents assigned to cards with lower values exhibit a lower willingness to pay for some non-wage characteristics, even though we should not expect valuations for the different attributes to change with the choices given to respondents. This shows that estimates using the payment card method are sensitive the values chosen by the researchers.

A final auxiliary experiment changes the value that was added or subtracted to the response given using the double bound method. Individuals were asked two binary questions - would you accept this job if it paid "X", and then a second question: "would you accept this job if it paid "X+Y" if they said no, or "X-Y" if they said yes. Appendix Table A9 reports includes dummy variables for the different values that are added or subtracted from the baseline wage. The estimates from column 1 & 2 are nearly identical, implying that the results are not sensitive to this parameter.

4 How do Amenity Values Differ by Gender?

A major benefit of being able to estimate the value of job attributes is the ability to understand how the value of these attributes differ by job seeker characteristics. Previous studies have shown that men and women have different preferences for attributes such as commute time (Le Barbanchon et al., 2020) and work flexibility (Mas and Pallais, 2017). We are able to expand on this earlier work by considering additional attributes like meals and childcare.

Table 5 presents the estimates of job attribute valuations from the discrete choice experiment for men and women separately. Column 1 includes estimates from using all the data we collected from the pooled sample. We have more than twice as many men in our sample as women, so confidence intervals for women tend to be larger.

The results show that men and women have different willingness to pay for some of the attributes we included in our survey. First, men have a 30% higher baseline wage than women. We also find that women require almost twice as much compensation to accept jobs that are further away from their homes relative to men.[17] We find suggestive evidence that women are more sensitive to working on weekends and value childcare more, but these estimates have wide confidence intervals and are not statistically different by gender.

Table A10 considers how valuations differ by gender using the other elicitation methods. While these methods are not well powered, and so most differences are not statistically significant, we compare the point estimates to get some idea of how the methods line up with our understanding of the labor market. For example, the open ended method finds very similar valuations across the two genders, but that men are more sensitive to long commute times, in contrast to earlier work that shows women are more sensitive to long commutes. The payment card method finds that women are more sensitive to commutes, but no difference in working on weekends and that women value daycare less than men. Finally the double bound finds practically no difference in commute preferences, but finds that women are more sensitive to working on weekends.

5 Policy Implications & Limitations

Our results lead to several important implications. First, estimated reservation wages and the valuation of job attributes are sensitive to the method used to elicit them. This is particularly important since the worst performing method to estimate reservation wages

[17] Christensen and Osman (2021) collect data on safety perceptions in this context and find that women are much more worried about the safety of their commutes relative to men.

(open ended questions) is the method that is most widely used in the literature (Krueger & Mueller, 2016). Scholars and practitioners would be better served using different methods, with discrete choice experiments performing best. While discrete choice experiments may seem more involved, they are also more intuitive to respondents, and only took 40 seconds longer to implement on average in our survey relative to the open ended questions commonly used in the literature.

Our results also speak to how valuation of job attributes differ by individual characteristics. This is directly relevant for efforts that try to increase labor force participation by underrepresented groups. By identifying which job attributes are most highly valued by individuals in those groups, policymakers could target those types of amenities through subsidies or direct regulation.

For example, we find evidence of differential valuing of commute time which is affected by government zoning policy. In many places, including in Egypt, policymakers have chosen to designate certain areas on the outskirts of the city as "industrial zones" where it is easier for companies to set up new businesses, while erecting barriers to opening new businesses in residential areas. Because of the disconnect between where people live, and where businesses are allowed to open, this increases commute times for employees, which in this context has a differential impact by gender, decreasing female labor force participation.[18] In fact, certain states in Egypt have identified this as an issue and have begun a program called "Your Job Next to Your Home" where the government has opened up more land in residential areas for business and factories to be built, to help address the issue of low levels of female labor force participation (Abdelaziz et al., 2016). Implementing these types of surveys on a larger and more varied sample can allow for a feasible way to estimate how different groups value different job amenities and provide policymakers with the ability to support particular groups with targeted regulations and subsidies (e.g. by subsidizing daycare, requiring schedule flexibility, etc.). These methods could be especially useful in developing country contexts where information frictions abound and knowledge of how different aspects of jobs are valued by different population groups is scarce.

[18]Egypt comes in as the 10th lowest out of 189 countries that the World Bank collects data for. India, for reference, is ranked 11th lowest and has a female labor force participation rate of 23.4%. Of the 10 countries with the lowest rates, 9 are in the Middle East North Africa region.

Another important way to utilize these results would be for firms to implement this type of measurement procedures with existing or potential employees. This can help firms craft bundles of amenities that are more in line with employee preferences. For example, if employees value certain perks that are less costly for the employer to provide than for the employee to provide for themselves (like meals, or daycare, or a gym, etc) then it may be worthwhile for the employer to begin incorporating those perks into the offer bundle to employees, even if that leads to a decrease in the overall salary provided. Linking these types of data with data on worker productivity could also provide an effective device to bring in the most productive workers (in line with the interview incentives provided in Abebe, Caria, and Ortiz-Ospina, 2019). Of course, these insights would only be useful if existing employer perceptions are out of sync with reality. Collecting data on employer perceptions could be a fruitful avenue for future research. Similarly, labor unions could use these methods to better identify which aspects of the job are most valuable for their members and utilize that information in their labor negotiations.

Finally, an example of how these ideas can be used in important business decisions, we can consider the choice of office location. Let us assume, for a particular firm, that office rent constitutes about 15% of firm costs, and labor constitutes about 30% of firm costs (not unreasonable assumptions). To determine which location is optimal requires knowing the percent discount that could come from moving to the outskirts, and the percent increase in labor costs from higher labor compensation. We find that moving from a 30 minute commute to a 90 minute commute would require increasing salaries by approximately 10%, or a total of 3% in firm costs. That would imply that it would be worth it for firms to move to the outskirts if they could secure a discount of at least 20% on their existing rent. True discounts for being further from the city center are likely higher than 20%, potentially explaining why so many firms do move outside of the city center. If a firm was able to find a 50% discount for moving away, this would decreases rent costs by 7.5%, while increasing labor costs by 3%, increasing overall profit margins by 4.5%. Net profit margins in many industries are below this amount.

Limitations

Our study has several limitations to consider. One important limitation is that our follow up survey does not provide bulletproof evidence regarding which of the methods performs best in the real world. While our estimates of how the valuation of job attributes differ across methods, and the DCE provides the estimates most consistent with the previous literature and our understanding of the labor market, this does not mean that it is correct. For example, we used the valuations placed on free meals and free daycare to disqualify measurement strategies that provided estimates that gave negative values to positive amenities. There is a chance that these amenities are seen as indicators of other aspects of the jobs that job seekers try to avoid. For example, maybe working at a place that has free meals is associated with a low prestige set of jobs that may also be dangerous or unpleasant. This would mean that the valuation we estimate includes both the benefit of the meals, but also the negative value of the other less enticing parts of the job, confounding our estimates. We did not instruct participants on how to think about the attributes of the jobs that were not listed in the questions and so we cannot rule this out. On the other hand, no participant asked about external factors which may imply that this was not on their mind. We also find that the estimated value of meals from the DCE lines up with the actual value of those meals if bought on the market in this context, which provides suggestive evidence that individuals were thinking primarily about the attribute and not what else it is correlated with.

Second, our estimates of the differences in the valuation of job attributes by gender are lower powered than we had anticipated. By replicating this analysis with a larger sample researchers would be able to more precisely showcase differences in valuation of job attributes by gender and other characteristics of interest such as education, marital status, etc.

Finally, our sample is comprised of individuals who have selected into working with a particular job matching center. The valuations that we estimate are going to be dependant on those in our sample. Our estimates about the differences between men and women may just be a difference between the men and women who use this job matching center. This issue of external validity is important in any study of a non-representative sample. We compare our sample to a representative survey, which allows us to show that our sample is similar to the general jobseeker population in our context. Nonetheless we cannot rule out that there may be important differences in unobservable characteristics.

6 Conclusion

Reservation wages and the value placed on non-wage job amenities are important parts of understanding labor market behavior of jobseekers. These parameters can help policymakers generate more effective employment tax and incentive schemes and help employers craft more efficient employee compensation bundles. Identifying which amenities are most valuable to underpresented groups in the labor market could help policymakers provide targeted subsidies that could encourage greater engagement by those groups. However, estimating the value that workers assign to job characteristics has proven challenging.

We find large differences in the estimates obtained using 4 different elicitation methods. Estimated reservation wages range from 1861EGP to 2515EGP. Estimated job amenity values can also differ widely by method. For instance the estimated compensating differential for working on the weekend ranges from EGP 326, or 13% of the baseline wage using open ended questions, to 134EGP or 6% of the baseline salary using pay-card elicitation.

Overall, our results show that estimates from the discrete choice experiment are preferred, since they are most consistent with our understanding of the labor market, basic economic theory, and estimates from other papers in the literature. There are many reasons why the DCE method works better, including being less susceptible to sequencing and anchoring effects. The psychology literature has identified other reasons why individuals may answer questions that attempt to recover the same underlying parameter differently (Tourangeau et al., 2000). This includes issues social desirability bias (Grimm, 2010) and cognitive uncertainty (Enke & Graeber 2021a, 2021b). Recent work has shown that when individuals feel more uncertain about their response this tends to lead them to responding in a way that is biased towards their "ignorance prior". In this case we expect more cognitive uncertainty in the three direct question methods since individuals may not know their reservation wage exactly, and less in the DCE exercise because it is easier for them to know which of the two job bundles they prefer, decreasing the amount of bias in their responses.

Future work could benefit from implementing these tests on different samples and with other job attributes. Finding a logistically feasible way to validate the results of these methods with a revealed preference approach using real jobs would be of high value. Validation exercises as in Mas and Pallais (2017) & He et al. (2021) are difficult to implement on a specific sample, whereas the methods outlined in this paper are easier to implement in a variety of contexts.

Collecting these data over time for the same set of job seekers would also be useful and could provide information on the dynamics of reservation wages as well as how valuations of different job attributes change over time. This could be valuable even after individuals find a job, as the value placed on certain amenities can change as people's work experience allow them to learn more about which amenities they value most in a job.

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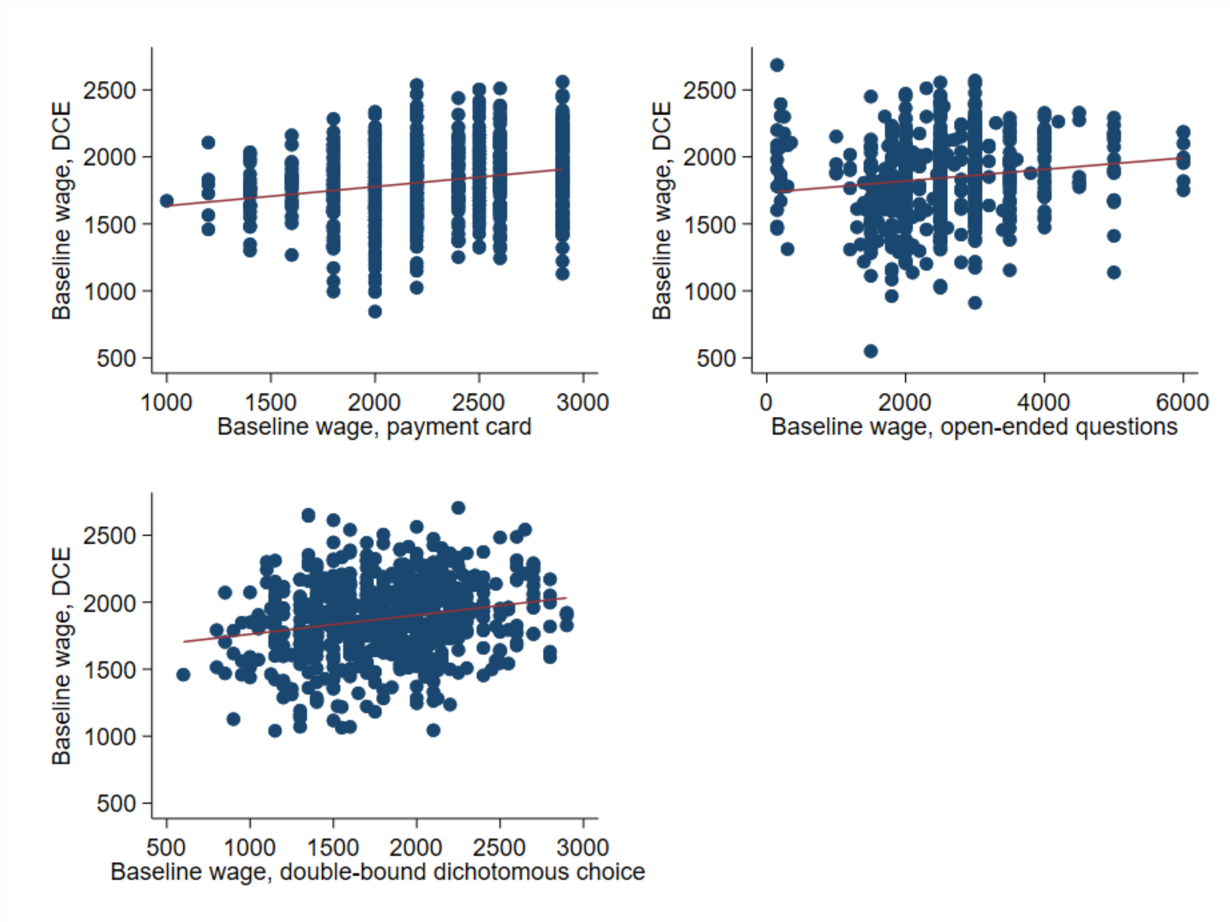
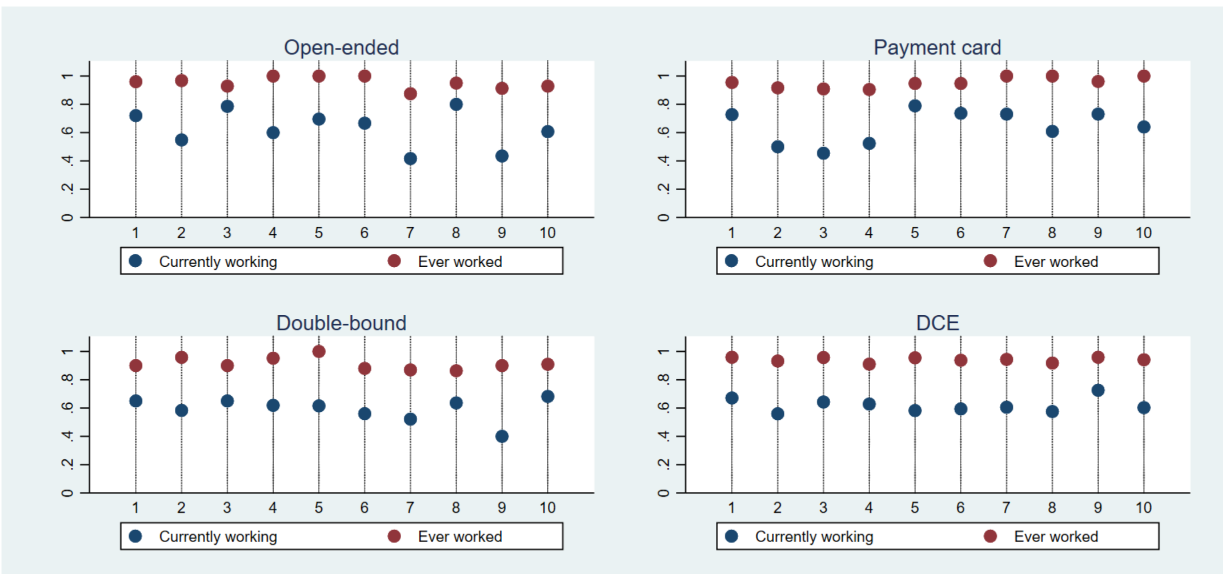
Figures and Tables

Figure 1: Correlation of reservation wages across methods



Note: The Figure shows the reservation wages estimated for each individual from the discrete choice experiment and the alternative elicitation method to which they were assigned. These reservation wages correspond to the minimum wage at which an individual would accept a job that is 30 minutes away from their home and has none of the attributes included in our survey. The correlation coefficients between the reservation wages estimated from the discrete choice experiment and the other elicitation methods are 0.14 in the case of the open-ended questions and 0.21 in the case of the payment card and double-bound dichotomous choice questions.

Figure 2: Probability of ever being employed by decile of reservation wage's residual



Note: The Figure shows the likelihood that a person ever worked since the baseline survey (red) and that of working at follow-up, for each decile of the residuals obtained from regressing baseline reservation wages obtained from each elicitation method on observable characteristics at baseline: gender, age, education, marital status, number of dependants, unemployment spell and search intensity. Larger residuals correspond to higher reservation wages than we would predict based on the individual's observable characteristics.

Table 1: Difference between estimated reservation wages by elicitation method

Panel A: Estimated Reservation Wages				
	Open Ended	Payment Card	Double Bound	Discrete Choice Experiment
	(1)	(2)	(3)	(4)
Reservation wage for baseline job	2515	2238	2045	1831
	(38.11)	(20.16)	(29.58)	(25.26)
Observations	4620	4704	4634	29940
Number of Individuals	660	672	662	1996

Panel B: P-Values for Pair-wise Comparisons of Reservation Wages			
	Payment Card	Double Bound	Discrete Choice Experiment
Open Ended	0.003	0.000	0.000
Payment Card		0.000	0.000
Double Bound			0.000

Note: Panel A reports estimated reservation wages using each method. Answers to open-ended are winsorized at the top and bottom 1%. The average reservation wage without winsorizing is EGP2711 (with a standard error of 157.77). Standard errors clustered at the individual level in parentheses. Panel B reports the p-value of the test that the wage at baseline is equal between the elicitation format depicted in the row title and the elicitation format in the column title.

Table 2: Estimates of willingness to pay for job attributes by elicitation method

	Open ended	Payment Card	Double Bound	Discrete choice experiment	DCE (1/3 sample)
	(1)	(2)	(3)	(4)	(5)
Commute time (60 Minutes)	182.59***	37.75	184.15***	98.31***	86.34***
	(55.53)	(40.00)	(51.63)	(21.53)	(31.84)
Commute time (90 Minutes)	273.37***	159.38***	190.25***	183.20***	167.29***
	(59.88)	(45.20)	(52.95)	(23.27)	(36.03)
Commute time (120 Minutes)	407.58***	67.63*	203.27***	259.76***	266.95***
	(62.93)	(35.67)	(53.36)	(25.90)	(37.05)
Health insurance (self)	-126.58***	-145.45***	-132.95***	-55.44***	-62.4***
	(29.14)	(19.07)	(35.64)	(13.42)	(22.40)
Health insurance (self & spouse)	-117.02**	-91.24***	-231.73***	-150.59***	-153.5***
	(45.66)	(30.37)	(22.70)	(14.97)	(25.76)
Need to work on weekends	325.41***	134.42***	233.71***	118.78***	132.15***
	(28.20)	(17.02)	(34.32)	(16.38)	(23.37)
Meals provided at workplace	83.82***	-18.12	-4.6	-84.43***	-74.97***
	(24.68)	(15.34)	(33.32)	(9.90)	(19.23)
Daycare provided at workplace	81.83***	-10.59	58.93*	-41.78***	-32.04*
	(24.66)	(17.20)	(33.47)	(11.22)	(19.49)
Observations	4620	4704	4634	29940	9990
Number of individuals	660	672	662	1996	666

Note: Each column reports the willingness to pay for each job attribute obtained from the different elicitation methods. Open-ended estimates were obtained by regressing the stated wage on indicators for each of the characteristics specified and winsorizing at the top and bottom 1% of responses. Payment card estimates were obtained by maximum likelihood where the dependent variable is the interval between the value chosen and the closest value available below the one chosen, using a model where all characteristics are interacted with a dummy that takes value 1 if the payment card shows a range of lower values. Double bound estimates were obtained by maximum likelihood using the intervals provided by the Yes/No answers to each job offer given by the respondent. Discrete choice experiment estimates were obtained using a mixed logit model in the willingness to pay space estimated by maximum likelihood. In column 5 we present the median estimates and standard errors of running the mixed logit on 287 randomly drawn subsamples of 1/3 of the respondents to match the sample size of the other elicitation methods. Standard errors clustered at the individual level between parenthesis.

*** $p<0.01$, ** $p<0.05$, * $p<0.1$

Table 3: Estimates of willingness to pay for job attributes by elicitation method using follow-up data

	Open ended	Payment Card	Double Bound	Discrete choice experiment
	(1)	(2)	(3)	(4)
Commute time (60 Minutes)	244.84***	-62.66	142.5	88.16*
	(91.67)	(60.60)	(96.97)	(49.97)
Commute time (90 Minutes)	264.87**	208.08***	247.53***	191.90***
	(105.48)	(73.71)	(84.44)	(30.90)
Commute time (120 Minutes)	450.27***	102.57*	235.42***	297.57***
	(94.80)	(55.23)	(81.40)	(54.60)
Health insurance (self)	-193.42***	-154.40***	-161.33**	-45.48**
	(61.03)	(37.72)	(62.96)	(19.57)
Health insurance (self & spouse)	-144.66**	-112.20***	-334.26***	-176.94***
	(65.34)	(41.04)	(35.93)	(47.98)
Need to work on weekends	392.87***	156.19***	218.26***	128.88**
	(64.14)	(43.37)	(64.39)	(58.08)
Meals provided at workplace	99.38**	-7.08	55.5	-70.96***
	(43.30)	(22.15)	(53.97)	(25.88)
Daycare provided at workplace	92.91**	6.77	101.53*	-64.16***
	(37.54)	(25.91)	(52.50)	(20.40)
Commute time (60 Minutes) × Current/last job	-68.37	84.96	163.1	-61.90
	(153.11)	(91.89)	(173.69)	(90.86)
Commute time (90 Minutes) × Current/last job	-363.88	-174.62	2989.6	-134.48***
	(352.21)	(199.32)	(10363.53)	(38.15)
Commute time (120 Minutes) × Current/last job	-1193.61***	102.90	-359.0	-465.90***
	(114.55)	(257.18)	(488.07)	(85.46)
Health insurance (self) × Current/last job	226.85**	-9.69	-46.3	-53.57
	(107.98)	(51.32)	(90.78)	(51.89)
Health insurance (self & spouse) × Current/last job	1726.51***	-246.82***	-31.7	126.85*
	(519.16)	(54.69)	(184.17)	(76.11)
Need to work on weekends × Current/last job	-120.45	-45.26	178.60*	43.04
	(106.84)	(53.51)	(92.20)	(66.71)
Meals provided at workplace × Current/last job	77.25	60.14	-51.0	-49.83
	(177.54)	(74.80)	(131.67)	(62.45)
Daycare provided at workplace × Current/last job	-199.35	.	15.4	-201.59***
	(421.16)	.	(289.00)	(62.66)
Reservation wage at baseline	2583	2285	2062	1924
Observations	2156	2114	1960	40095
Number of Individuals	308	302	280	891

Note: Each column reports the willingness to pay for each job attribute obtained from the different elicitation methods at baseline when we include interactions between the attribute and whether the respondent's most recent job includes that attribute when re-interviewed. Open-ended estimates were obtained by regressing the stated wage winsorized at the top and bottom 1% (Column 1) on indicators for each of the characteristics specified. Payment card estimates were obtained by maximum likelihood where the dependent variable is the interval between the value chosen and the closest value available below the one chosen, and includes interactions between each characteristic and a dummy that takes value 1 if the payment card shows a range of lower values. Double bound estimates were obtained by maximum likelihood using the intervals provided by the Yes/No answers to each job offer given by the respondent. Discrete choice experiment estimates were obtained using a mixed logit model in the willingness to pay space estimated by maximum likelihood. Reservation wage at baseline corresponds to average salary when the job is 30 minutes away from the respondent's home and no other attribute is included. None of the individuals found at follow up among those who were initially assigned to the payment card method had a job with daycare and so that parameter could not be estimated. Standard errors clustered at the individual level between parenthesis. *** p<0.01, ** p<0.05, *p<0.1

Table 4: Sensitivity of responses to question sequencing

	MLE (1)	OLS (chosen) (2)	OLS (midpoint) (3)
Health insurance (self)	-147.060***	-72.824***	-90.486***
	(19.267)	(13.242)	(14.042)
Health insurance (self & spouse)	-136.481***	-50.455***	-72.773***
	(22.312)	(15.494)	(16.441)
Health insurance (self) × Treatment	-15.011	-31.111*	-24.085
	(27.293)	(18.640)	(19.721)
Health insurance (self & spouse) × Treatment	-111.704***	-69.781***	-73.159***
	(32.532)	(21.414)	(23.045)
P-value of no effect for interaction terms	0.000	0.003	0.002
Observations	5,982	5,982	5,982
Number of individuals	1994	1994	1994

Note: The table shows pooled estimates from the open ended, payment card and double bound dichotomous choice depending on whether the baseline (first) job shown includes health insurance for the respondent and their spouse. "Treatment" indicates that the first job offered included health insurance for the respondent and their spouse, the second job offer only included health insurance for the respondent, and the third offer did not include health insurance. When that indicator takes the value of zero, the order of the job offers is reversed. In column 1 estimates are obtained from an interval regression via maximum likelihood (for open-ended questions the lower and upper bound are the same value, which correspond to the answer given by the respondent). In column 2 we obtained estimates using OLS, and in the case of payment card and double-bound dichotomous choice we take the value chosen by the individuals (for the double-bound dichotomous choice method, we take the lowest value accepted by the respondent, or the highest value shown if no offer was accepted). In column 3, we obtain our estimates via OLS using the midpoint of answers for the case of the payment card and double-bound dichotomous choice methods. P-value of no effect for interaction terms refers to the joint test of significance of the two interaction terms. Standard errors clustered at the individual level between parenthesis.

*** p<0.01, ** p<0.05, *p<0.1

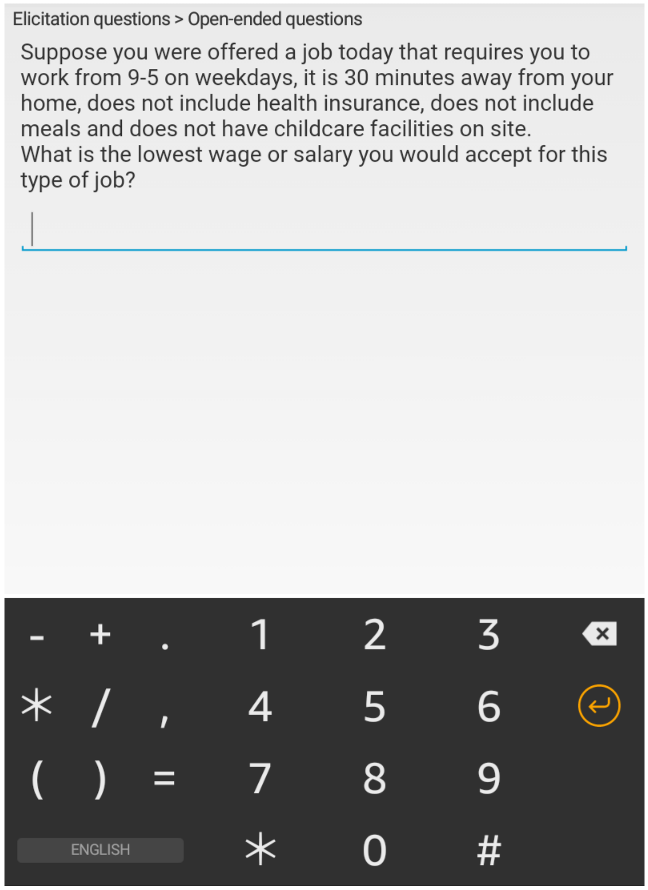
Table 5: Discrete choice experiment estimates split by gender

	Pooled sample	Men	Women	P-value of difference
	(1)	(2)	(3)	(4)
Commute time (60 Minutes)	98.31***	75.69***	166.31***	0.06
	(21.53)	(21.12)	(45.10)	
Commute time (90 Minutes)	183.20***	158.53***	266.83***	0.30
	(23.27)	(33.97)	(87.30)	
Commute time (120 Minutes)	259.76***	251.60***	439.21***	0.08
	(25.90)	(19.56)	(107.35)	
Health insurance (self)	-55.44***	-65.38***	-27.4	0.32
	(13.42)	(17.77)	(34.99)	
Health insurance (self & spouse)	-150.59***	-154.62***	-120.37**	0.56
	(14.97)	(17.88)	(55.51)	
Need to work on weekends	118.78***	118.53***	172.93***	0.26
	(16.38)	(20.42)	(38.89)	
Meals provided at workplace	-84.43***	-61.63***	-95.8	0.64
	(9.90)	(22.22)	(73.84)	
Daycare provided at workplace	-41.78***	-12.7	-114.8	0.46
	(11.22)	(10.63)	(136.74)	
Reservation wage at baseline	1831	1919	1581	0.01
Observations	29940	21075	8865	
Number of Individuals	1996	1405	591	

Note: Column 1 shows the estimates of willingness to pay for different job attributes obtained from the discrete choice experiment on the full sample of survey respondents. Columns 2 and 3 present the results for men and women separately, and column 4 shows the p-value of the difference in valuation for each attribute across gender. Reservation wage at baseline corresponds to average salary when the job is 30 minutes away from the respondent's home and no other attribute is included. The number of observations corresponds to the number of individual-choice pairs. Standard errors clustered at the individual level between parenthesis.
*** p<0.01, ** p<0.05, *p<0.1

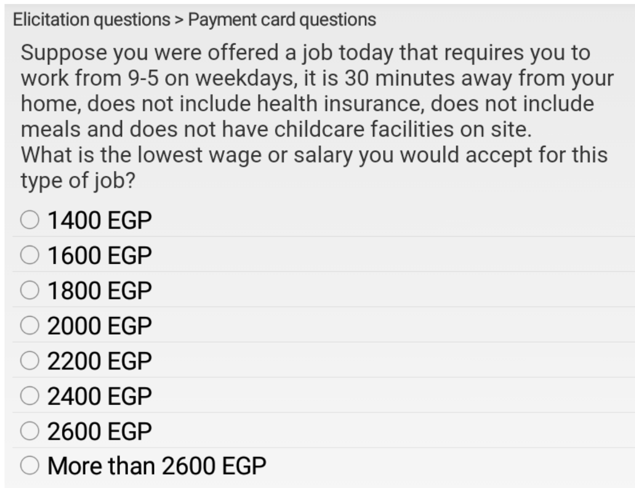
Appendix A Additional Figures and Tables

Figure A1: Example of open-ended question asked to respondents



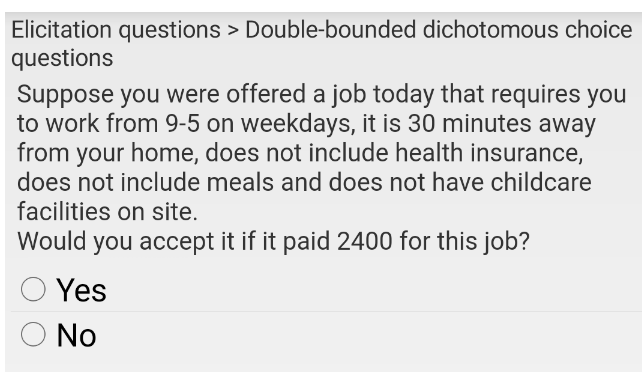
Note: The Figure shows an example of the questions that individuals assigned to the open-ended elicitation format faced. The original version was in Arabic to facilitate the respondent's understanding of the task

Figure A2: Example of payment card question asked to respondents



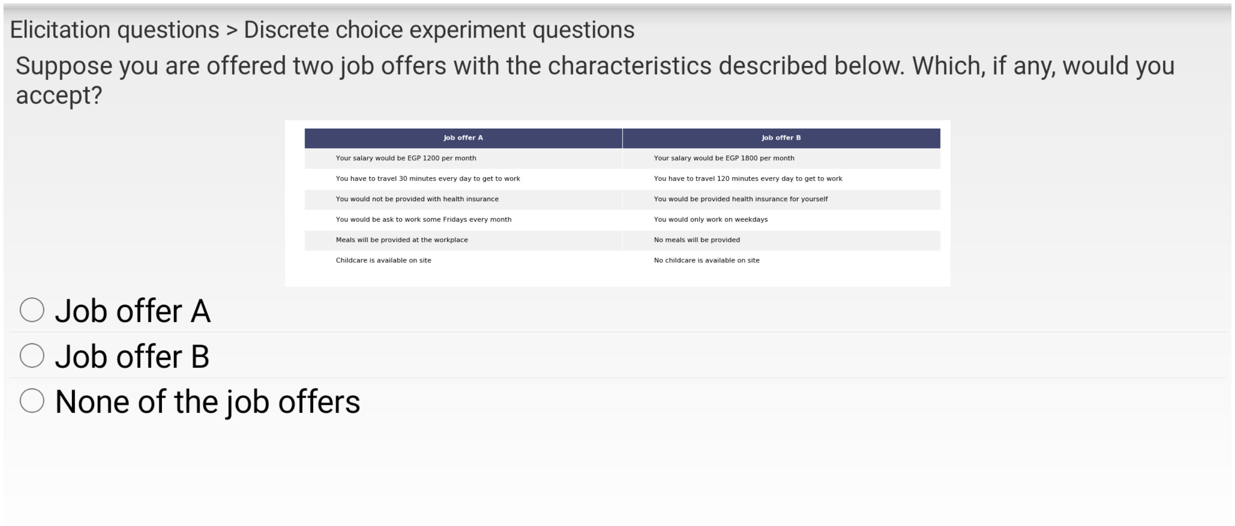
Note: The Figure shows an example of the questions that individuals assigned to the payment card elicitation format faced. The original version was in Arabic to facilitate to facilitate the respondent's understanding of the task

Figure A3: Example of double-bound dichotomous choice question asked to respondents



Note: The Figure shows an example of the questions that individuals assigned to the double bound dichotomous choice elicitation format faced. The original version was in Arabic to facilitate the respondent's understanding of the task

Figure A4: Example of discrete choice question asked to respondents



Elicitation questions > Discrete choice experiment questions

Suppose you are offered two job offers with the characteristics described below. Which, if any, would you accept?

Job offer A	Job offer B
Your salary would be EGP 1200 per month	Your salary would be EGP 1800 per month
You have to travel 30 minutes every day to get to work	You have to travel 120 minutes every day to get to work
You would not be provided with health insurance	You would be provided health insurance for yourself
You would be ask to work some Fridays every month	You would only work on weekdays
Meals will be provided at the workplace	No meals will be provided
Childcare is available on site	No childcare is available on site

- Job offer A
- Job offer B
- None of the job offers

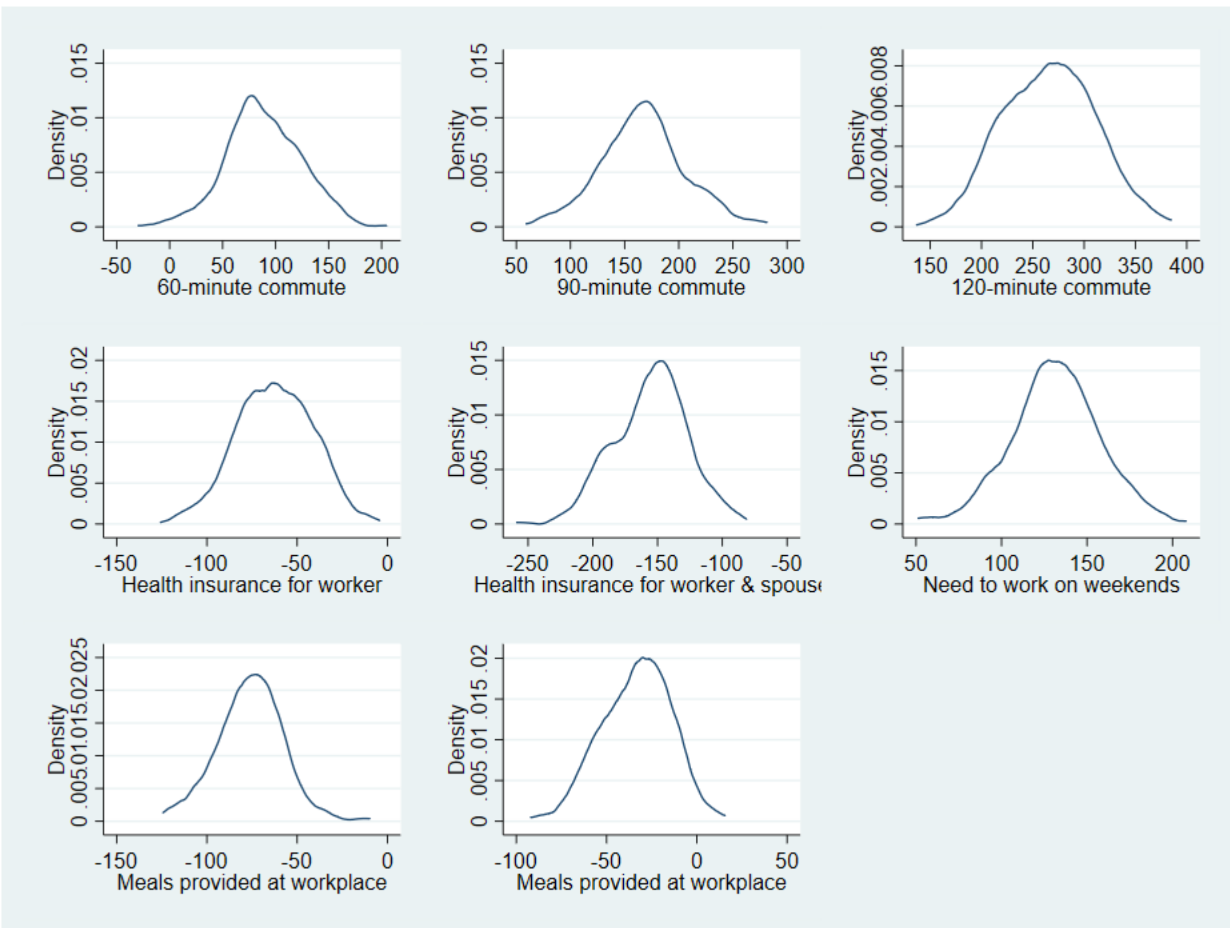
Note: The Figure shows an example of the questions that individuals faced when completing the discrete choice experiment. The original version was in Arabic to facilitate the respondent's understanding of the task.

Table A1: Job attributes included in the survey and their values

Attribute	Levels
Commute time (one-way)	30 minutes 60 minutes 90 minutes 120 minutes
Included health insurance	No For the worker For the worker and spouse
Need to work on weekends	No Some weekends
Meals provided	No Yes
On-site daycare	No Yes

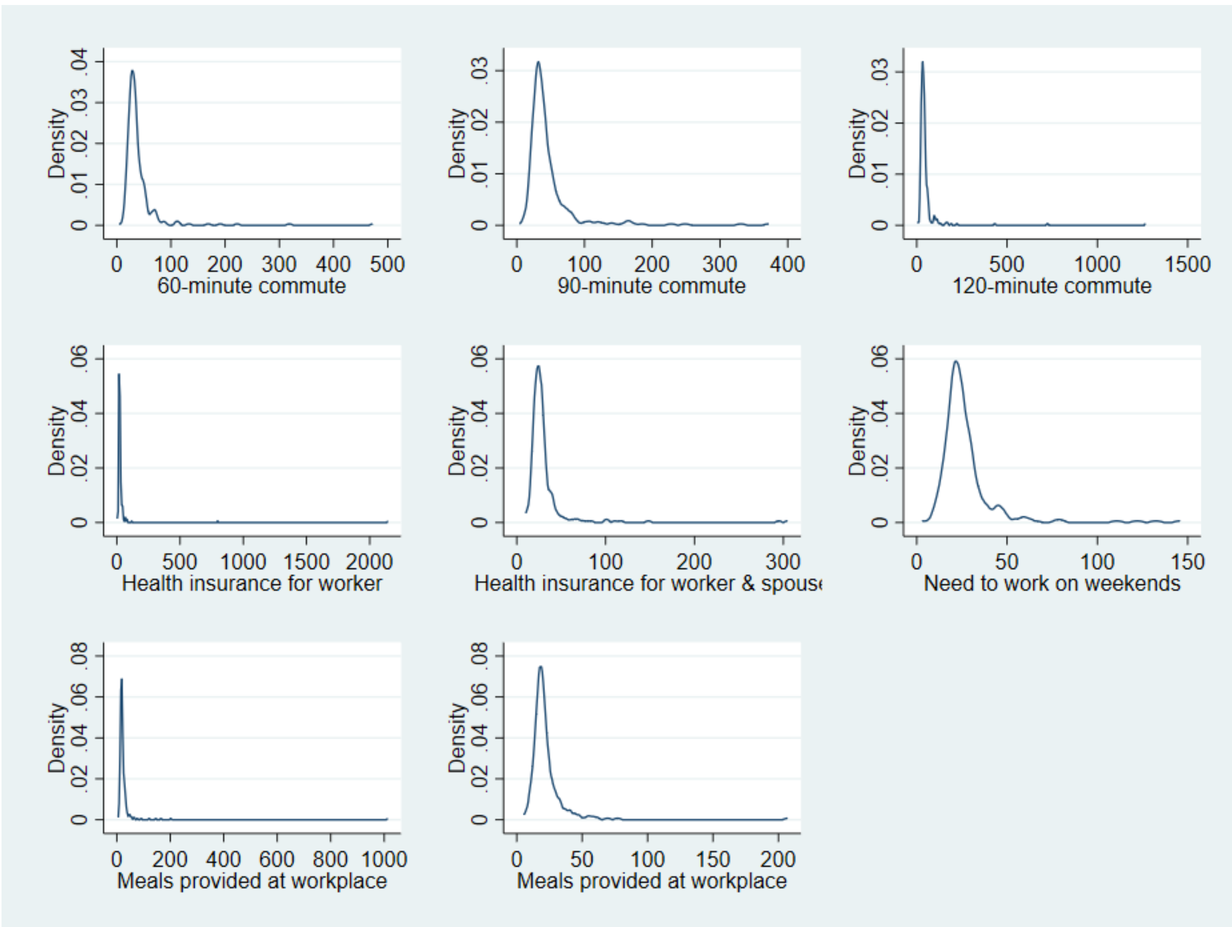
Note: The table shows the different job attributes that could vary in the hypothetical job offers presented to a respondent. Except in the case of the Discrete Choice Experiment, only one job attribute was varied at a time with each offer shown.

Figure A5: Distribution of coefficients of WTP for job attributes obtained from the DCE subsamples



Note: The Figure shows the empirical distribution of estimates for each job attribute obtained from the discrete choice experiment from the 287 random subsamples taken to match the sample size of the other three elicitation formats used.

Figure A6: Distribution of standard errors of WTP estimates for job attributes obtained from the DCE subsamples



Note: The Figure shows the empirical distribution of the standard errors of the estimates for each job attribute obtained from the discrete choice experiment from the 287 random subsamples taken to match the sample size of the other three elicitation formats used.

Table A2: Summary statistics of survey respondents and comparison with 2017 Labor Force Survey

Panel A: Survey Participants	All			Men			Women		
	Mean	SD	N	Mean	SD	N	Mean	SD	N
Age	26.64	6.19	1996	27.27	6.28	1405	25.15	5.73	591
Share male	0.70	0.46	1996						
Share married	0.29	0.46	1637	0.30	0.46	1159	0.28	0.45	478
Number of dependents	0.87	1.20	1637	0.91	1.26	1159	0.78	1.04	478
Years of education	12.83	4.00	1637	12.78	3.93	1159	12.94	4.18	478
Unemployment spell (months)	8.27	16.54	1628	8.00	16.55	1143	8.92	16.51	485
Hours spent last week looking for a job	20.41	20.32	1679	21.67	20.80	1175	17.47	18.86	504
Hours spent on average looking for a job	14.31	15.86	1679	15.70	16.75	1175	11.07	13.01	504
Number of methods used to look for a job	1.70	1.56	1996	1.69	1.60	1405	1.72	1.47	591

Panel B: 2017 Labor Force Survey	All			Men			Women		
Age	25.62	6.32	8826	24.71	6.27	4661	26.66	6.23	4165
Share male	0.53	0.50	8826						
Share married	0.24	0.43	8826	0.10	0.30	4661	0.40	0.49	4165
Years of education	12.47	3.82	8826	11.79	4.19	4661	13.23	3.17	4165
Unemployment spell (months)	32.98	35.78	8826	24.08	25.44	4661	43.14	42.55	4165
Number of methods used to look for a job	2.28	1.40	8826	2.37	1.44	4661	2.18	1.35	4165

Note: Panel A shows the mean and standard deviation for demographic characteristics and job search behavior of our survey respondents. Sample size for each characteristic vary depending on our ability to match data from our respondents to that collected by our partner NGO. Panel B presents the corresponding demographic characteristics and search behavior (if available) according to unemployed individuals in the 2017 Labor Force Survey. Hours spent looking for a job and unemployment spell variables winsorized at the bottom and top 5%.

Table A3: Sample characteristics and baseline balance

	Mean for assigned to open-ended format (1)	Assigned to payment card format (2)	Assigned to double-bound dichotomous choice format (3)
Age	26.642	-0.329	0.337
		(0.339)	(0.340)
Share male	0.722	-0.023	-0.032
		(0.025)	(0.025)
Share married	0.311	-0.035	-0.018
		(0.028)	(0.028)
Number of dependents	0.866	-0.052	0.070
		(0.073)	(0.073)
Years of education	12.884	0.045	-0.214
		(0.242)	(0.243)
Unemployment spell (months)	9.071	-1.650	-0.747
		(1.000)	(1.004)
Hours spent last week looking for a job	21.355	-1.210	-1.648
		(1.211)	(1.216)
Hours spent on average looking for a job	14.590	-0.888	0.053
		(0.945)	(0.949)
Number of methods used to look for a job	1.749	-0.102	-0.047
		(0.086)	(0.086)
P-value of joint test		0.429	0.389
Observations	660	672	662

Note: Each row presents the mean of the covariate for the individuals assigned to the open-ended formats and the coefficients of a regression of the covariate on indicators that take the value of one if the individual was assigned to the payment card (Column 2) or double-bound dichotomous choice elicitation format (Column 3). P-value of joint test refers to the test that covariates do not jointly determine assignment to treatment.
Standard errors between parenthesis.
*** $p<0.01$, ** $p<0.05$, * $p<0.1$

Table A4: List of questions used in open-ended, payment card & double bound methods

1. Suppose you were offered a job today that requires you to work from 9-5 on weekdays, it is 30 minutes away from your home, does not include health insurance, does not include meals and does not have childcare facilities on site. What is the lowest wage or salary you would accept for this type of job?
2. Suppose you were offered a job today that requires you to work from 9-5 on weekdays, it is 30 minutes away from your home **it offers health insurance for you**, but does not include meals or health insurance on site. What is the lowest wage or salary you would accept for this type of job?
3. Suppose you were offered a job today that requires you to work from 9-5 on weekdays, it is 30 minutes away from your home **it offers health insurance for you and your spouse**, but does not include meals or childcare facilities on site. What is the lowest wage or salary you would accept for this type of job?
4. Suppose you were offered a job today that requires you to work from 9-5 on weekdays, **it is *X* minutes away from your home**, does not include health insurance, does not include meals and does not have childcare facilities on site. *(The value X was randomized so that individuals only saw one value of either 60, 90, or 120).* What is the lowest wage or salary you would accept for this type of job?
5. Suppose you were offered a job today that requires you to work from 9-5 on weekdays **and requires you to work on Friday instead of a weekday twice a month**, it is 30 minutes away from your home, does not include health insurance, does not includes meals and does not have childcare facilities on site. What is the lowest wage or salary you would accept for this type of job?
6. Suppose you were offered a job today that requires you to work from 9-5 on weekdays, it is 30 minutes away from your home, does not include health insurance, **includes meals at work**, and does not have childcare facilities on site. What is the lowest wage or salary you would accept for this type of job?
7. Suppose you were offered a job today that requires you to work from 9-5 on weekdays, it is 30 minutes away from your home, does not include health insurance, does not include meals, **but has on-site childcare facilities**. What is the lowest wage or salary you would accept for this type of job?

Note: This table reports the questions used in the Open Ended, Payment Card, and Double Bound Dichotomous Choice methods for preference elicitation. The questions were the same in each method, the only difference was the response options, as outlined in Section 2. The differences between each scenario is **bolded**. In the case of open ended questions, the respondent has to enter an integer to respond. For payment card questions, the respondent is asked to choose a value from a list shown below each question. For the dichotomous choice questions, the question shown is replaced by 'Would you accept it if it paid $\$Z$ for this job?", where Z is a salary chosen at random from a pre-specified list.

Table A5: Estimates of open-ended elicitation method with winsorized values

Cutoff	0%	1%	2%	5%
	(1)	(2)	(3)	(4)
Commute time (60 Minutes)	152.79	182.59***	179.72***	171.92***
	(123.20)	(55.53)	(52.56)	(41.50)
Commute time (90 Minutes)	148.58	273.37***	272.55***	241.82***
	(105.51)	(59.88)	(57.31)	(46.25)
Commute time (120 Minutes)	303.77***	407.58***	379.32***	307.46***
	(107.82)	(62.93)	(57.58)	(45.58)
Health insurance (self)	-301.43***	-126.58***	-117.68***	-95.06***
	(105.16)	(29.14)	(27.84)	(20.91)
Health insurance (self & spouse)	-221.99**	-117.02**	-108.38**	-88.68**
	(86.21)	(45.66)	(43.26)	(34.70)
Need to work on weekends	320.68***	325.41***	315.77***	279.73***
	(109.39)	(28.20)	(26.58)	(19.30)
Meals provided at workplace	14.46	83.82***	81.83***	73.21***
	(87.46)	(24.68)	(23.54)	(16.90)
Daycare provided at workplace	-45.10	81.83***	83.62***	75.38***
	(77.37)	(24.66)	(23.82)	(17.86)
P-value of equality of coefficients		0.000		
Wage at baseline (EGP)	2711	2517	2506	2520
Observations	4620	4620	4620	4620
Number of Individuals	660	660	660	660

Note: The table shows estimates from the open ended elicitation format when responses are unwinsorized (column 1), and winsorized at the 1, 2 and 5% of the bottom and top of the distribution of responses (columns 2 to 4, respectively). Baseline wage corresponds to the average salary when the job is 30 minutes away from the respondent's home and no other attribute is included. Standard errors clustered at the individual level between parenthesis. *** p<0.01, ** p<0.05, *p<0.1

Table A6: Relationship between the probability of being found at follow-up and elicitation method assigned at baseline

	Resurveyed (1)
Assigned to payment card	-0.017
	(0.027)
Assigned to double bound dichotomous choice	-0.024
	(0.028)
Constant	0.508***
	(0.019)
Observations	1,994
R-squared	0.000

Note: The table shows the relationship between being found in the follow-up survey and the elicitation method to which the respondent was assigned at baseline. The base group corresponds to individuals assigned to the open-ended elicitation method. The dependent variable is an indicator that takes the value of one if the person was found at follow-up.
*** $p<0.01$, ** $p<0.05$, *$p<0.1$

Table A7: Baseline determinants of the probability of being found at follow-up

Dependent variable: Found at follow-up	Open Ended (1)	Payment Card (2)	Double Bound (3)
Male indicator	0.137**	0.023	-0.082
	(0.055)	(0.078)	(0.077)
Age	0.001	-0.001	-0.001
	(0.005)	(0.007)	(0.007)
Reservation wage estimated from DCE	-0.076	0.008	0.153
	(0.070)	(0.104)	(0.102)
Married indicator	0.040**	-0.025	-0.039
	(0.018)	(0.025)	(0.025)
Education level	0.036	-0.002	-0.046
	(0.029)	(0.043)	(0.039)
Number of dependants in the household	0.001	0.000	0.001
	(0.001)	(0.002)	(0.002)
Job search spell, in months	-0.000	0.000	0.000
	(0.000)	(0.000)	(0.000)
Constant	0.216	0.105	0.053
	(0.213)	(0.303)	(0.303)
P-value of H0: No differential attrition		0.992	0.397
Observations		1326	

Note: Each column presents the estimates from the interaction of each observable characteristic with an indicator that takes the value of one if the individual was assigned to the corresponding elicitation method at baseline. The base group corresponds to individuals assigned to the open-ended elicitation method. The dependent variable is an indicator that takes the value of one if the person was found at follow-up. The lower sample size with respect to our main results is due to lack of data on certain baseline characteristics for some respondents.
*** p<0.01, ** p<0.05, *p<0.1

Table A8: Comparison of estimation methods for the payment card format

	Interval (1)	Chosen value (2)	Midpoint (3)
Commute time (60 Minutes)	37.75	14.85	39.33
	(40.00)	(34.04)	(37.51)
Commute time (90 Minutes)	159.38***	117.25***	145.33***
	(45.20)	(35.00)	(40.77)
Commute time (120 Minutes)	67.63*	47.24	55.23
	(35.67)	(30.28)	(35.41)
Health insurance (self)	-145.45***	-137.95***	-142.72***
	(19.07)	(16.67)	(19.02)
Health insurance (self & spouse)	-91.24***	-77.06***	-89.52***
	(30.37)	(26.03)	(29.74)
Need to work on Friday	134.42***	116.15***	132.10***
	(17.02)	(14.58)	(17.60)
Meals provided at workplace	-18.12	-31.23**	-24.29
	(15.34)	(13.58)	(15.69)
Daycare provided at workplace	-10.59	-23.38	-10.34
	(17.20)	(15.20)	(17.36)
Lower card values	-255.79***	-273.37***	-256.15***
	(38.35)	(31.83)	(36.44)
60-Minute commute x Low card values	7.20	19.51	1.31
	(55.32)	(45.47)	(50.34)
90-Minute commute x Low card values	-63.95	-44.85	-64.02
	(59.19)	(45.40)	(52.42)
120-Minute commute x Low card values	73.21	54.12	60.79
	(55.08)	(42.07)	(49.42)
Health insurance (self) x Lower card values	85.19***	91.35***	88.16***
	(26.03)	(21.53)	(24.59)
Health insurance (self & spouse) x Lower card values	45.29	44.23	49.90
	(41.92)	(34.35)	(39.14)
Need to work on Friday x Lower card values	-21.01	-32.10*	-33.56
	(23.86)	(19.20)	(22.58)
Meals x Lower card values	86.78***	84.80***	83.81***
	(22.54)	(18.57)	(21.50)
Daycare x Lower card values	21.94	32.13	19.25
	(23.71)	(20.17)	(23.17)
Wage at baseline (30 min to work, no other attribute)	2238	2291	2215
P-value of no effect for interaction terms	0.000	0.000	0.000
Observations	4704	4704	4704
Number of Individuals	672	672	672

Note: The table shows the results obtained from using different methods to estimate the willingness to pay for job attributes among individuals assigned to the payment card format. Column 1 shows the estimates for each attribute from the payment card elicitation using an interval regression, where the range is bounded between the value chosen by the respondent and the value immediately below. Column 2 uses the value chosen by the individual, while column 3 uses the midpoint of the range. Standard errors clustered at the individual level between parenthesis.
*** p<0.01, ** p<0.05, *p<0.1

Table A9: Comparison of estimates for the double-bound dichotomous choice format

	Pooled sample (1)	Pooled sample (2)
Commute time (60 Minutes)	182.14***	184.15***
	(51.65)	(51.63)
Commute time (90 Minutes)	191.17***	190.25***
	(52.95)	(52.95)
Commute time (120 Minutes)	203.00***	203.27***
	(53.35)	(53.36)
Health insurance (self)	-133.53***	-132.95***
	(35.64)	(35.64)
Health insurance (self & spouse)	-232.40***	-231.73***
	(22.67)	(22.70)
Need to work on weekends	233.32***	233.71***
	(34.33)	(34.32)
Meals provided at workplace	-4.3	-4.62
	(33.34)	(33.32)
Daycare provided at workplace	59.22*	58.93*
	(33.48)	(33.47)
Wage changes of 200EGP		43.28
		(33.81)
Wage changes of 300EGP		62.08*
		(34.51)
Wage changes of 400EGP		8.37
		(34.60)
Wage changes of 500EGP		-28.31
		(33.90)
Reservation wage at baseline	2045	1985
Observations	4634	4634
Number of Individuals	662	662

Note: Column 1 shows the estimates for each attribute using the double bound method without controlling for the size of the random wage increase\decrease the individual was allocated to. Column 2 includes controls for each group. Standard errors clustered at the individual level between parenthesis.
*** p<0.01, ** p<0.05, *p<0.1

Table A10: Treatment effect heterogeneity by gender across elicitation methods

	Open Ended			Pay Card			Double Bound		
	Men	Women	P-value of difference	Men	Women	P-value of difference	Men	Women	P-value of difference
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
Commute time (60 Minutes)	171.44***	184.47*	0.92	77.36**	-24.56	0.07	183.19***	177.00**	0.96
	(64.12)	(103.19)		(31.05)	(46.78)		(62.45)	(90.02)	
Commute time (90 Minutes)	295.99***	260.77***	0.77	120.19***	157.33***	0.53	203.33***	195.85**	0.95
	(74.01)	(94.68)		(35.22)	(47.11)		(65.96)	(87.22)	
Commute time (120 Minutes)	448.24***	291.81***	0.23	70.96**	113.27**	0.49	178.89***	234.65**	0.63
	(74.78)	(105.69)		(28.99)	(53.67)		(63.47)	(95.36)	
Health insurance (self)	-120.72***	-138.64***	0.76	-113.37***	-82.66***	0.24	-95.34**	-204.23***	0.15
	(36.39)	(44.56)		(15.55)	(21.28)		(43.37)	(61.68)	
Health insurance (self & spouse)	-110.30**	-128.05	0.85	-78.02***	-44.94	0.44	-246.32***	-201.49***	0.35
	(54.40)	(77.81)		(23.50)	(35.91)		(27.37)	(39.32)	
Need to work on weekends	304.35***	379.30***	0.22	116.97***	133.08***	0.55	184.59***	331.78***	0.04
	(34.40)	(49.62)		(13.70)	(22.99)		(41.34)	(59.70)	
Meals provided at workplace	83.68***	82.73**	0.98	14.6	36.85*	0.36	-9.4	4.91	0.84
	(31.63)	(36.65)		(13.66)	(19.87)		(40.15)	(58.33)	
Daycare provided at workplace	79.32**	86.92**	0.87	-11.4	21.29	0.19	56.1	68.14	0.87
	(31.87)	(35.20)		(14.50)	(20.30)		(40.51)	(58.10)	
Lower card values				-228.89***	-147.39***	0.17			
				(33.87)	(49.44)				
Wage at baseline	2637	2200		2342	1988		2144	1839	
Observations	3332	1288		3290	1414		3199	1435	
Number of Individuals	476	184		470	202		457	205	

Note: The table shows estimates of the value for each job characteristic by elicitation method used, for men and women separately. Open-ended estimates correspond to estimates of the winsorized sample at the top 1%. Payment card estimates correspond to the specification in which each attribute is interacted with a dummy that takes value 1 if the payment card shows a range of lower values. Baseline wage corresponds to average salary when the job is 30 minutes away from the respondent's home and no other attribute is included. Standard errors clustered at the individual level between parenthesis.
*** $p<0.01$, ** $p<0.05$, *$p<0.1$