Wage Differentials and the Price of Workplace Flexibility

Marshall Drake
Boston University

Neil Thakral
Brown University

Linh T. Tô
Boston University

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Abstract

This paper studies the interplay between how much workers value workplace flexibility, whether they have such amenities, and how the presence of amenities affects their wages. To overcome the challenge of eliciting quantitative measures of willingness to pay (WTP) at the individual level, we propose the use of dynamic choice experiments, a method which we call the Bayesian Adaptive Choice Experiment (BACE). We implement this method to collect data on the joint distribution of wages, work arrangements, and WTP for different forms of flexibility. We then introduce and estimate a model in which workers may face different prices for job amenities depending on their productivity, extending the Rosen (1986) model of compensating differentials. The model captures key patterns in the data, including (i) the relationship between wages and having amenities, (ii) inequality in workplace amenities across the earnings distribution even when workers value these amenities similarly, and (iii) the tradeoffs across different forms of flexibility. We use the estimates to explore the welfare consequences of workers facing different amenity prices.

*Drake: Department of Economics, Boston University, 270 Bay State Road, Boston, MA 02215 (email: mhdrake@bu.edu). Thakral: Department of Economics, Brown University, Box B, Providence, RI 02912 (email: neil_thakral@brown.edu). Tô: Department of Economics, Boston University, 270 Bay State Road, Boston, MA 02215 (email: linhto@bu.edu). The study was approved by the Institutional Review Board at Brown University (Protocol #1911002579).

1 Introduction

Technological and organizational changes in the US and across the world have the potential to alter the structure of work as the costs of providing workplace amenities shift over time. A prominent example widely discussed in the media is how improved communication technologies and the Internet allow companies to provide their employees with better workplace flexibility.[1] The ongoing pandemic further highlights the important interplay between workers' demand for workplace attributes and employers' costs of providing them.

To understand how wage and non-wage job attributes are traded off, the seminal theory in labor economics is that of compensating differentials (Rosen, 1986). In this research paper, we aim to shed light on the relationship between the wage structure and the incidence of amenity provision by incorporating the idea that firms' cost of providing an amenity may not be the same for all workers. In particular, we build on the classic Rosen (1986) model by allowing firms' costs of providing amenities to vary with worker productivity. This is consistent with the idea that "flexibility complements a production process that relies on monitoring outputs rather than worker inputs... with higher-skilled workers having more demanding workplaces that emphasize their output over their inputs" (Mas and Pallais, 2020). The equilibrium in this model involves sorting of workers with high willingness to pay (WTP) for amenities into jobs at firms with low costs of providing those amenities. Combining our model of firms' costs with the full distribution of workers' preferences therefore fully characterizes the labor market equilibrium, which enables us to evaluate policy counterfactuals and measure welfare.

Estimating the model requires the joint distribution of wage and willingness-to-pay at the individual level, and we contribute a new discrete choice experimental method, Bayesian Adaptive Choice Experiment (BACE), to efficiently elicit this previously-unknown information. BACE makes it possible to obtain individual-level preference estimates while accommodating flexible underlying utility functions and a broad range of designs of the choice experiments. In addition, the method significantly

[1]See, for example, Bayern (2019).

improves efficiency and overcomes biases in existing approaches.

Empirically, we focus on amenities related to work hours and workplace flexibility. We estimate the model using survey data that we collect, combining individual-level willingness to pay for job amenities that we elicit using BACE with information on wages and other job attributes. A key insight from our model is that, conditional on WTP, workers sort based on productivity. Eliciting individual-level WTPs thus enables us to infer equilibrium amenity prices as a function of worker productivity. Our findings from a survey of participants on the online research platform Prolific show that the distributions of workers' valuation of amenities related to workplace flexibility are highly skewed, with thick tails of workers, particularly women, who consider workplace flexibility very important in their job choice. We also document substantial bias that arises from taking the standard approach of pooling the data across respondents to estimate the average valuation because of such skewness.

We estimate the model and explore the welfare consequences of workers facing different amenity prices. We extend the model to the case with multiple amenities to understand why women are not more likely to be in flexible jobs despite valuing them more, and are instead in jobs with fewer hours and lower wages. Following the policy debate of whether the government should regulate or subsidize firms to provide workplace flexibility (Council of Economic Advisors, 2010, 2014), we also evaluate policy counterfactuals based on our model and estimates.

The idea that different aspects of employment compensate for each other dates back to Adam Smith's *"The Wealth of Nations"*. The theory of compensating wage differentials formalized by Rosen (1974, 1986) explains how the underlying structure of pay differs across workers: In a frictionless labor market where all jobs are available to all workers, the allocation of workers to jobs reflects preferences for non-wage amenities (Rosen, 1986). Across an enormous subsequent literature, many empirical studies have documented that higher wages are often associated with better job amenities, raising difficulties in estimating compensating differentials. This has "led some (e.g., Hornstein, Krusell and Violante 2011) to conclude that compensating differentials are not likely to prove important for understanding overall earnings inequality" (Sorkin, 2018).

Incorporating heterogeneity in firms' cost of amenity provision by worker productivity provides a novel explanation for the absence of compensating differentials in past studies and sheds new light on the wage structure. For example, the model rationalizes why there is a positive correlation between wages and the presence of location and schedule flexibility in the jobs, but a negative correlation between wages and the ability to work fewer hours at the same pro-rated wage rate. The model can also be extended to explain trade-offs across amenities by firms and workers, such as the association between high hours and more flexible jobs, which has implications for the gender gap in wages. By contrast, these phenomena do not arise in models emphasizing the failure of detecting compensating differentials due to factors such as search frictions (Hwang, Mortensen and Reed, 1998; Dale-Olsen, 2006; Bonhomme and Jolivet, 2009), imperfect competition (Lang and Majumdar, 2004), and unmeasured worker and firm characteristics (Hwang, Reed and Hubbard, 1992).

This research paper contributes to two influential strands of work in the recent literature on compensating wage differentials. One set of papers attempts to characterize equilibrium amenity prices, i.e., the *WTP of the marginal worker*, by estimating the slope of the hedonic pricing function using observational data (Lalive, 2003; Tsai, Liu and Hammitt, 2011; Lavetti and Schmutte, 2018). Another set of papers uses Discrete Choice Experiments (DCEs) that randomly vary job characteristics to isolate the tradeoffs that workers face to obtain estimates of the *average WTP* for amenities (Eriksson and Kristensen, 2014; Mas and Pallais, 2017; Wiswall and Zafar, 2018; Maestas et al., 2018). Papers in the first strand consider equilibrium outcomes, which are pinned down by marginal workers (and firms), thus providing only limited information on valuations for other workers. Characterizing overall *inequality in the labor market* requires estimates of the average WTP. While the second set of papers delivers estimates of this object, a model of the supply side is required to characterize the market equilibrium price for job amenities and conduct counterfactual analyses. By eliciting individual-level WTP estimates, our research unifies these strands of research. Estimating the full WTP distribution enables us to (1) assess to what extent differences in the incidence and valuation of nonwage job characteristics shape inequality in the labor market, (2) characterize the contribution of variation in amenity prices to inequality, and (3) use an equilibrium model to analyze the effects of various counterfactual policies.

2 Bayesian Adaptive Choice Experiment

Understanding preferences is a crucial input into economic models. Yet, for many important policy questions, preferences cannot be reliably inferred using observational data. While revealed preference has been a important tool for economists, this approach has proven to be limited in some important economic environments. Well-acknowledged limitations include the strong modeling assumptions and data availability required to infer individual preferences, the inability to learn about non-use values, and the unobserved factors, market imperfections, and behavioral biases that can present serious confounds when inferring preferences using observational data. This has led to a proliferation of research using stated preference approaches such as Discrete Choice Experiments (DCEs) to estimate individual preferences in a broad range of applications. These include studies in labor economics (Mas and Pallais, 2017), public economics (Neustadt and Zweifel, 2011), health economics (Ryan, Gerard and Amaya-Amaya, 2007), environmental economics (Carson and Czajkowski, 2014), development economics (Jeuland et al., 2009), agricultural economics (Schulz, Breustedt and Latacz-Lohmann, 2014), urban economics (Bullock, Scott and Gkartzios, 2011), education (Czajkowski et al., 2020), psychology (Ida and Goto, 2009), criminology (Picasso and Cohen, 2019), real estate (Glumac and Wissink, 2018), transportation (Bliemer and Rose, 2011), and marketing (Green, Krieger and Wind, 2001). In economics, DCEs have become increasingly popular, with one of the more common uses in recent years being the measurement of workers' preferences for job attributes (Eriksson and Kristensen, 2014; Mas and Pallais, 2017; Wiswall and Zafar, 2018; Maestas et al., 2018; Mas and Pallais, 2019; Gelblum, 2020; Feld, Nagy and Osman, 2020), which is also our application in this paper. Beyond the academic literature, these methods feature prominently in policy analysis, regulation, and litigation (Carson, 2012).

A standard Discrete Choice Experiment (DCE) asks respondents to choose among a set of alternatives that vary along multiple dimensions. Without a dynamic framework, these alternatives consist of pre-generated, randomized bundles of characteristics. The resulting lack of statistical power to infer preferences at the individual level typically necessitates a focus on estimating average preferences when using static approaches. This has several notable shortcomings: (1) it requires making assumptions about the preference distribution in the population as well as implicit assumptions about homogeneity in respondents' inconsistency in making choices; and (2) it can lead to biased estimates of average preferences, related to the mean-variance confound in estimating limited dependent variable models using maximum likelihood (Yatchew and Griliches, 1985).

BACE provides an efficient dynamic elicitation procedure for conducting choice experiments that overcomes these problems. It does so by generating an efficient sequence of choice scenarios based on a prior that gets updated with previous answers to obtain individual-level Bayesian posterior estimates. At each stage of experimentation, the next scenario to be presented is the one that will yield the greatest information gain about the parameter values, including a choice consistency parameter. The procedure thus allows for an efficient elicitation of preferences for each individual, taking into account heterogeneity in choice inconsistency.

The increasing use of hypothetical choice experiments in economics and related fields has helped provide evidence and support for the reliability of the method. Existing research shows that estimates from choice experiments are often in reasonable ranges and with expected signs (Mas and Pallais, 2017; Maestas et al., 2018); consistent across different subject pools (Mas and Pallais, 2017); consistent with subsequent choices (Wiswall and Zafar, 2018; Aucejo, French and Zafar, 2021); and superior to estimates from other types of survey questions such as open-ended questions and multiple price list, which tend to be noisy and inconsistent with basic economic theory (Feld, Nagy and Osman, 2020). In fact, when comparing four elicitation methods (discrete choice experiment, open-end questions, pay card / multiple price list, and double bounded dichotomous choice questions), Feld, Nagy and Osman (2020) find that only with the DCE is there no valuation that is inconsistent with economic theory. BACE then provides a timely and important improvement for a reliable method that has been proving its usefulness and can be applied broadly by many researchers.

While adaptive designs for choice experiments have been proposed in previous research, the biggest barrier to implementation outside of university computer laboratories using student subjects has been computational costs. In Drake, Thakral and Tô (2022), we provide an implementation of BACE that is portable, scalable, and computationally feasible and provide a more detailed description of the properties of BACE. The code allows a survey platform (Qualtrics) to interact with on-the-cloud backend servers that can do large-scale computation of the next-best scenario simultaneously across survey subjects in real time. This results in a practical approach that can be made into a package for other researchers to easily apply the method to different settings to address a wide range of questions.

The idea of optimal experimental design to estimate parameters efficiently dates back to Peirce (1967), and Wald (1950) describes the idea of dynamic designs in statistics. While the concept is widespread in many fields in the physical and biological science, it is not often discussed and rarely implemented in economics (see Aigner 1979; Moffatt 2007; Chapman et al. 2018 for further discussion). The most common application in economics and psychology so far has been the elicitation of time and risk preferences (Cavagnaro et al., 2013; Toubia et al., 2013; Cavagnaro et al., 2016; Chapman et al., 2018; Imai and Camerer, 2018), though the implementations there are largely limited to small-scale within-the-lab versions or as coarse pre-computed approximations to the Bayesian-optimal dynamic elicitation.[2] We contribute to this literature in two ways. First, our implementation makes a step forward in allowing such procedures to be more widely adopted to study a wide range of other possible social science applications. Second, we document systematic biases in estimating average preference parameters from commonly used static approaches.

[2]In the context of a correspondence study, Avivi et al. (2021) consider the efficiency gain from dynamically adapting the profiles of fictitious applicants sent to employers. A related but distinct literature explores adaptive procedures with a different objective, namely, to maximize the gain from experimental treatments while measuring treatment effects; recent papers include Caria et al. (2020) and Kasy and Sautmann (2021).

2.1 Methodology

A standard discrete choice experiment involves presenting a set of hypothetical scenarios which allows subjects to evaluate tradeoffs between two choices at a time. These scenarios are typically randomly generated across a range of values.[3] The adaptive Bayesian approach to the standard discrete choice experiment generates an efficient sequence of hypothetical scenarios in real-time based on a prior that gets updated with past answers. At each stage of experimentation, the next scenario to be presented is the one that will generate the highest amount of information gained about the parameter values. In a simple search model when subjects evaluate the value of one parameter against a benchmark one at a time, the most efficient approach is a binary search. The adaptive Bayesian approach has the same principle as a binary search, but it allows for complex search problems with multiple dimensions and the fact that choices may be made inconsistently because of inattentiveness.

The BACE procedure is as follows; we first introduce some notation. At each period $t \in \{1, 2, \dots\}$, a choice scenario d_t^* is presented and respondent's answer x^t (conditional on d_t^*) is recorded. The set of past answers up to t, corresponding to the questions asked so far, is our data at the beginning of period $t+1$, denoted as $x^{(1:t)} \equiv \{x^1, \dots, x^t\}$. Let θ be the parameter vector of interest. At the beginning of period $t+1$, our prior for θ is denoted as $\Pr\left(\theta \,\middle|\, x^{(1:t)}\right)$.

The problem at time $t+1$ is to find the optimal d_{t+1}^* among all possible scenarios d_{t+1}s. The criterion chosen is based on information theory, such that we maximize the mutual information between the parameter random value Θ and the outcome random value X^{t+1} (the potential answer at $t+1$) conditional on the scenario d_{t+1} (Shannon, 1948). The interpretation is that we find the next hypothetical scenario to present that yields the largest information gain about the parameters upon the observation

[3] In many cases, scenarios that involve an ex-ante pre-determined dominated choice are eliminated to increase statistical power, such as in Wiswall and Zafar (2018); Maestas et al. (2018).

of a new answer.[4] Denote this mutual information as $U(d_{t+1}) \coloneqq I(\Theta; X^{t+1}|d_{t+1})$:[5]

$$U(d_{t+1}) = \int_\theta \int_{x^{t+1}} \left[\log \frac{\Pr\left(\theta \,\middle|\, x^{(1:t+1)}, d_{t+1}\right)}{\Pr(\theta \mid x^{(1:t)})} \right] \Pr\left(x^{t+1} \,\middle|\, \theta, d_{t+1}\right) \Pr\left(\theta \,\middle|\, x^{(1:t)}\right) dx^{t+1} d\theta \tag{1}$$

In the language of the Bayesian experimental design literature (Chaloner and Verdinelli, 1995), this is the utility function of the researcher and the objective is to find $d^*_{t+1} = \arg\max_{d_{t+1}} U(d_{t+1})$.

Note that $\Pr(x^{t+1} \mid \theta, d_{t+1})$ is the likelihood of the answer x^{t+1} given the presented scenario d_{t+1}, at parameter value θ, which can be computed from the utility function. In the case of testing across utility models, the formula above also needs to summarize over all the candidate models. The posterior $\Pr\left(\theta \,\middle|\, x^{(1:t+1)}, d_{t+1}\right)$ can be computed given the likelihoods and the prior using Bayes' rule. The posterior is then updated based on the realized answer:

$$\Pr\left(\theta \,\middle|\, x^{(1:t+1)}, d_{t+1}\right) = \frac{\Pr(x^{t+1} \mid \theta, d_{t+1}) \Pr\left(\theta \,\middle|\, x^{(1:t)}\right)}{\int_{\theta'} \Pr(x^{t+1} \mid \theta', d_{t+1}) \Pr(\theta' \mid x^{(1:t)}) d\theta'} \tag{2}$$

Figure 1 shows the schematic illustration of the steps involved. The procedure starts with some prior distribution $p(\theta)$ which can either be a uniform distribution over the parameter space, or is based on a previous experiment.

2.2 Implementation

There are two main implementation challenges. First is the computational burden of computing the optimal next-best scenario, and second is the ability to conduct the

[4] Paninski (2005) shows that if the prior is absolutely continuous and has bounded density, the mutual information criterion can choose designs that lead to consistent and efficient parameter estimates. Alternative criteria include maximizing the inverse of the asymptotic covariance matrix of the maximum likelihood estimate as in Toubia et al. (2013) or the Equivalence Class Edge Cutting information criterion as in Imai and Camerer (2018), among others; see Ryan et al. (2016) for a review.

[5] The mutual information is the same as the Kullback-Leibler divergence between the joint distribution and the product of the marginal distributions of Θ and $X^{t+1}|d_{t+1}$.

adaptive procedure flexibly for a wide range of subjects beyond the lab. We overcome these challenges and implement the method with thousands of survey respondents in real time.

The computational difficulties can be seen from the formula in Equation (1), where we are faced with a multi-dimensional integration problem that does not have a straightforward analytical solution. The general framework allows for complete flexibility over the space of scenarios, possible answers, and the parameter space, but the main challenge remains computational. In practice, the scenario space can be discretized, and a binary answer choice is standard in DCEs given its simplicity for respondents. The number of parameters then determines the complexity of the numerical integration problem. With four or fewer parameters, which can accommodate many standard applications, a grid-based approach can work well, though better approaches including Monte Carlo methods can be used with higher dimensions (Press et al., 2007). In our current implementation, we use adaptive resampling criteria using similar ideas to sequential Monte Carlo methods (Smith, 2013). Future work will continue to refine the computation method and allow for flexible trade-offs between speed and precision. The computational burden is reduced with the recognition that the required components, which are the likelihoods of any given answer in any particular scenario for a fixed set of parameter values, can be pre-computed.

There are two approaches to implementing the next-best scenario. One is pre-compute the decision tree, which requires computational resources upfront, memory to store the tree itself, and communication between the survey interface and the look-up tree. The other is to compute the next-best scenario in real time if such computation can be done within seconds. Our current implementation is the latter, but it can also be modified easily to accommodate the former. The main implementation innovation is the ability to do all the computation using back-end servers and databases with simultaneous communication between the survey platform and the servers, eliminating computer requirements beyond standard Internet speeds on the user side. We develop code to allow a survey platform (Qualtrics) to interact with on-the-cloud backend servers that can do large-scale computation of the next-best scenario simultaneously across survey subjects in real time; Figure 13 provides a schematic summarizing the interactions between the survey platform, backend server, and database in our implementation. This enables a fully dynamic elicitation outside of university laboratory settings in which subject pools typically consist of students. Our method can also be applied to use other survey platforms such as mobile texting devices, which would bypass the Internet requirement and allows for further outreach of this methodology, especially in developing country contexts.

2.3 Simulation validation

Our current simulations highlight two notable econometric advantages of the BACE method to elicit preferences. First, BACE allows for a much higher precision of the parameter estimates with fewer scenarios presented to each subject. Second, the standard approach of estimating the average preference parameter by pooling together scenarios and answers across subjects may result in biased estimates, which can be avoided when taking the average of the individual-level preferences from a BACE procedure (Drake, Thakral and Tô, 2022).

We compare across two methods to generate the sequence of scenarios: the adaptive Bayesian approach (BACE), and a procedure where sequences are randomly generated (RAND). We also interact each method to generate the scenarios with one of two evaluation approaches: using Bayesian updating, and using a maximum likelihood estimator (MLE). Given the answer choices and the set of scenarios, one can Bayesian update the parameter distribution using Equation (2), or one can pool together the data and find the estimate that maximizes the likelihood of the data obtained based on Equation (3).

2.3.1 Efficiency

We start with the case when the two job scenarios only differ by one amenity. We first specify the utility function that determines choice. In each hypothetical scenario, two jobs $j \in \{0, 1\}$ are presented that the subject can choose from. The jobs consist of earnings y_j, and whether amenity a_j is at the base value ($a_j = 0$) or the alternative value ($a_j = 1$). Utility from job j is $u_j = \log(y_j) + \beta_i a_{ij}$. Willingness to pay for the alternative over the base value of amenity a_i as a fraction of y_0 can be easily derived to be $\exp(\beta_i) - 1$.

Without choice inconsistency, the individual always chooses the bundle with the higher utility. Since inconsistency may arise in practice, we consider two cases for modeling choices. In case 1, the probability of making a "mistake" is higher when the two bundles are closer in total utility; in this case, "mistake" is represented by an error term in the utility function that has a Gumbel distribution with scale parameter β (lower β represents higher consistency). In case 2, with a fixed probability p, the individual chooses randomly instead of choosing the higher-utility bundle (lower p represents higher consistency). In this case, subjects choose the job with the higher utility, but with $p \in [0, 1]$ chance of being inattentive, which we define as the probability of picking a choice at random instead.[6] The probability of choosing $x = j$ is then

$$\Pr(x = j \mid \theta \equiv \{\beta_i\}, d \equiv \{j, 1 - j\}) = (1 - p)\mathbf{1}_{\left\{\log(y_j/y_{1-j}) + \left(\beta_i(a_{ij} - a_{i(1-j)})\right) > 0\right\}} + p/2 \tag{3}$$

The formulas above can be easily extended to incorporate multiple amenities or interaction terms between amenity values.

Figure 4 shows that regardless of the evaluation method, the adaptive Bayesian approach yields more information about the utility function parameter faster. When the likelihood of being inattentive is below 50 percent, the procedure can lead to relatively precise estimates with 5 to 10 questions. Figure 5 shows that the correlation between the true parameters and the estimated ones approaches 1 much faster with the adaptive method. Between Bayesian updating and MLE, Bayesian updating has the edge, and it performs significantly faster.

In the next set of simulations, we consider a binary choice experiment under two different utility models, each with four parameters. The two utility models consist of

[6] This formation mirrors Mas and Pallais (2017) who model an across-subject inattentive rate in a similar way.

the same preference parameters but differ based on how choice inconsistency operates. In both cases, the preference parameters are of the form $u_j = \log(y_j) + \beta_1 a_{1j} + \beta_2 a_{2j} + \gamma a_{1j} a_{2j}$ where j is the index of a chosen bundle of attributes described by (y_j, a_{1j}, a_{2j}), $y \in \mathbb{R}$, $a \in \{0, 1\}$. Without choice inconsistency, the individual always chooses the bundle with the higher utility. Since inconsistency may arise in practice, we consider two cases for modeling choices as before.

In the two-amenity case, the story is much similar qualitatively, with the adaptive Bayesian approach gaining ground even more relative to the random approach. Figures 6 to 9 show that the amenity value coefficients continue to perform well with 10 questions or fewer. Figure 6 also shows that the Bayesian estimation procedure gives more precise estimates compared to using a standard maximum likelihood estimator, in which a numerical optimization procedure is required to compute the estimates. We also note that BACE yields a substantial improvement in mean squared error for estimating the interaction term when more scenarios are asked when there is a higher degree of choice consistency, but this is not the case for RAND (see Figures 7 and 9). The interaction coefficient also shows significant gains from using BACE relative to RAND. Figures 10 and 11 show that one would need about 15 to 20 questions to achieve high precision with the adaptive Bayesian approach, and would need at least 3 times more questions with the random approach for the same level of precision. According to the simulations, presenting 10 scenarios using BACE gives more precise estimates than presenting 50 or more scenarios in a randomly generated sequence. Given that one can trade off between the interaction term and either of the two amenity coefficients, it is clear that the interaction term is harder to identify. The simulation results also show that Bayesian updating performs more consistently than MLE.

The online Appendix further shows that the method is robust to different ways to model inattentiveness. For example, even if the individual makes more mistakes when utility difference is smaller, for example, we are still able to recover the utility parameters well.

2.3.2 Bias

In Figure 12, we evaluate the importance of obtaining individual-level preferences even when the object of interest is the average preference in the population.[7] We find that the standard approach of pooling together responses across individuals to estimate the average preference results in possible bias, even with large samples when the sample mean follows a normal distribution. This is true regardless of whether one uses scenarios and answers from BACE or RAND.

This is reminiscent of the mean-variance confound described in Yatchew and Griliches (1985). Intuitively, individuals may have heterogeneous tendencies to make inconsistent choices, and it is difficult to account for individual heterogeneity in choice inconsistency when combining all individual data in the estimation with a combined error term, leading to bias.

To elaborate, consider the simple case when each individual n make choices based on the following data generating process. The latent variable for choice i is $u_i = \alpha_n w_i + \beta_n z_i + \epsilon_i$, with w_i and z_i randomly drawn and ϵ_i being independent and identically distributed according to a logistic distribution. The outcome variable is $y_i = \mathbf{1}_{\{u_i>0\}}$. Because of the normalization involved (either the variance of the error term, or one of the coefficients), we are interested in β_n/α_n for each individual n. An alternative normalization is $u_i = w_i + \frac{\beta_n}{\alpha_n} z_i + \frac{1}{\alpha_n}\epsilon_i$. Now u_i is measured in units of w_i and $\frac{1}{\alpha_n}$ is the scale of the error term (inconsistency in choices).

Assume that $i = 1, \ldots, I$ data points are collected for each individual n. Running a logit regression of y_i on w_i and z_i for each individual n should result in consistent estimates of α_n and β_n. However, when I is small, we sometimes pool together all data points across individuals and estimate y_i on w_i and z_i to obtain estimates α and β. When α_n and β_n vary across individuals: α and β do not recover the average of α_ns and average of β_ns, nor can we recover the average β_n/α_n. In some cases, the pooled estimate may even be outside the range of individual-level parameters. Of course, if α_n is the same across individuals, then we do recover the average of the β_ns

[7] See Drake, Thakral and Tô (2022) for further investigation of this issue.

3 Data on WTP and Job Characteristics

3.1 Experimental design

Our implementation of BACE can dynamically process many subjects at the same time. We collect data from about 1,000 survey respondents on the online research platform Prolific. We restrict the respondents to be those based in the US, speak fluent English, whose age is between 18 and 64. We ask respondents about their demographics and the characteristics of their jobs, as well as elicit their WTP for three workplace amenities: the ability to work from home (Location Flexibility), the ability to arrange one's schedule (Control over Schedule), and the ability to work fewer hours at the same wage rate (Part-time for Part-pay Option). The baseline alternative in each case is the absence of the amenity.

Another innovation that we introduce in our survey is providing a simple and easy-to-implement incentive based on the survey respondents' demand for information about the surveys they take. While working on the platform is a small side job for the majority of survey respondents, there is an incentive to do the job well, and there is no inherent incentive for distortion (as might be the case, for example, when real workers try to appease potential employers by altering statements about their preferences). Nevertheless, we randomize three-quarters of the respondents to an incentive treatment in which they are told near *the beginning of the survey* that their answers will be used to show them more information about their preferences as well as how they compare to others. Figure 14 provides a summary of the details of the experimental design.

The incentive causes a statistically significant increase of 7 percent in time spent answering the survey questions, as Figure 16 shows. To demonstrate the value of this information to respondents, we also present non-incentivized respondents the end of the survey with the option to view the information. We find that information demand is high, with 75 percent opting to view the information despite having to "pay" for it with their time.

3.2 Willingness-to-pay data

The characteristics of our sample are similar to the CPS, as Appendix Figure 1 shows. In our main specifications, we use sample weights based on the CPS so that the characteristics are representative, but the unweighted results shown in the Appendix are similar.

Figure 17 shows that the WTP estimates that we elicit are reasonable.[8] A small fraction of WTP estimates are negative, indicating that these workers would rather avoid the flexibility option. However, these WTP estimates are consistent with qualitative written responses to open-ended questions asking for reasons why they want the amenity or why they would not want the amenity. In Table 3, workers mention self-control and commitment as reasons to prefer not having flexibility options, consistent with findings in Mas and Pallais (2017). This corroborates the validity of our estimation method. In addition, Figure 18 shows that the estimates are stable across questions.

The distributions of WTP are highly skewed. There is a thick tail of workers who put very high value on workplace flexibility options, particularly female workers—which we can detect due to having individual-level WTPs. Importantly, the preferences of individuals in the tail of the distribution is relevant for characterizing the labor market equilibrium, which depends on the preferences of the marginal worker (and costs of the marginal firm). We also confirm in our data that the standard approach of pooling together data across individuals to estimate the average WTP results in more extreme estimates that are skewed toward the tails (see Figure 19).

In Figure 20, the data show a clear pattern of sorting by WTP, with higher-WTP workers being more likely to have the amenity. However, the relationship between wages and having an amenity is more complex: it is not always consistent with the basic idea that workers who forgo having amenities are compensated in terms of wages (even when we control for observables), but rather depends on the amenity considered. In particular, we see that wages are positively correlated with having control over work location and schedule, but negatively correlated with having the

[8] See Figure 1 for unweighted estimates.

ability to work fewer hours at the same pay rate.

4 Model of Amenity Prices

We present a model of compensating differentials in which workers may not all face the same amenity price. In particular, we extend the classic Rosen (1986) model so that amenity prices may depend on worker productivity.

Before presenting the details of the model, we note that allowing prices to vary across workers provides an explanation for two key patterns in the data. First, willingness-to-pay alone is not sufficient to explain who has or does not have the amenity, as workers do not sort perfectly into jobs based on their willingness to pay for job amenities. For example, college workers tend to have schedule and flexible Location more often, despite not valuing them more, and schedule and flexible Location incidence is similar by gender, despite females valuing them more. Second, having the amenity can be positively or negatively correlated with wage, controlling for education and other covariates (e.g., positive in the case of flexible location, and negative in the case of flexible total hours).

An important ingredient of our model is that firms' costs of providing amenities depends on worker productivity. The recent survey article by Mas and Pallais (2020) mentions the possibility that firms' costs may vary by workers' types: "flexibility complements a production process that relies on monitoring outputs rather than worker inputs. . . with higher-skilled workers having more demanding workplaces that emphasize their output over their inputs." In addition, "differences in job characteristics can be thought of as components of different production processes for higher skill work. . . flexibility is cheaper for employers to provide in higher-skilled jobs." This assumption is also consistent with the ideas discussed by Goldin (2014): "if there are transaction costs that render workers imperfect substitutes for each other, there will be penalties from low hours depending on the value to the firm." Moreover, "Workplace flexibility is a complicated, multidimensional concept. The term incorporates the number of hours to be worked and also the particular hours worked, being 'on call,' providing 'face time,' being around for clients, group meetings, and the like... idiosyncratic temporal demands are generally more important for the highly-educated workers."

The main implication of our model is that equilibrium amenity prices vary with worker productivity, and therefore workers no longer sort perfectly based on willingness to pay. However, conditional on worker WTP, workers sort based on productivity. This allows us to estimate the model to infer equilibrium amenity price as a function of worker productivity, given the joint joint distribution of wages, work arrangements, and WTP for amenities that we elicit using BACE.

The basic version of our model when we consider tradeoffs between wages and one binary amenity highlights the innovations we make to the classic Rosen (1986) framework. We then proceed to introduce the more general version of the model that we estimate, which allows for tradeoffs among different amenities.

4.1 One amenity

Amenities Consider a single binary non-wage job characteristic ("amenity") denoted n.

Productivity and wages Worker productivity has an observed component ω and an unobserved component θ. We denote the worker's productivity as $\pi = \omega + \theta$. Unobserved productivity is distributed $\theta \sim G$. The worker's productivity is unobserved to the econometrician but known to the worker and the firm when wages are set.

In our model, the *amenity price* is a function of productivity, denoted $p(\pi)$; this is distinct from the fixed amenity price in Rosen (1986). *Wages* are set based on productivity net of the amenity price due to compensating differentials. Thus, wages are given by $w = \pi - p(\pi)n + \epsilon$, where we assume that $\epsilon \sim \mathcal{N}(0, \sigma)$. The idiosyncratic term may represent an idiosyncratic match-specific productivity shock, i.i.d. across jobs and across periods. Wages and prices are measured in logs.

Firms (costs) There is a unit mass of firms. Each firm j faces a per-period cost of providing the amenity. We assume that the cost of providing the amenity is monotonic in the worker's productivity π, and we allow for heterogeneity across firms in the form of a cost shifter $f_j \sim F$. The cost of providing the amenity is thus $c_j(\pi) = f_j + k(\pi)$, where $k(\pi)$ is monotonic. *Firms' rents* are given by $(p(\pi) - c_j(\pi))n$.

Workers (preferences) There is a unit mass of workers. A worker's utility function is $u = w + xn$, where x denotes the worker's WTP (preference) for the amenity. Let H denote the distribution of worker amenity preferences, which we take to be known. *Workers' rents* are given by $(x - p(\pi))n$.

Amenity prices (equilibrium) In a perfect-sorting equilibrium, amenity prices satisfy a *market-clearing condition*: the supply of jobs with the amenity should coincide with the demand for jobs with the amenity. At price $p(\pi)$, a firm will provide the amenity to workers of productivity π if and only if $c_j(\pi) \leq p(\pi)$, or equivalently $f_j \leq p(\pi) - k(\pi)$. The fraction of firms that are willing to provide the amenity at price $p(\pi)$ is thus $F(p(\pi) - k(\pi))$. Analogously, since workers demand the amenity if and only if $x \geq p(\pi)$, the fraction of productivity π workers willing to accept a job with the amenity is $1 - H(p(\pi) \mid \pi)$.

The market clearing condition thus requires that $F(p(\pi) - k(\pi)) = 1 - H(p(\pi) \mid \pi)$. Differentiating both sides with respect to π (assuming the appropriate differentiability conditions) and rearranging gives

$$p'(\pi) = \frac{f(p(\pi) - k(\pi))}{f(p(\pi) - k(\pi)) + h(p(\pi) \mid \pi)} k'(\pi),$$

which (given the assumption that $k(\pi)$ is monotonic) leads to the following proposition: The equilibrium amenity price $p(\pi)$ is monotonic in worker productivity. In particular, the equilibrium amenity price is increasing in worker productivity if and only if firms' cost of providing the amenity is increasing in worker productivity. While this result is straightforward to prove, it demonstrates that the comparative statics of equilibrium amenity prices are independent of the distribution of workers' preferences and instead reflects the firms' cost function. In other words, under perfect sorting, inferring equilibrium amenity prices will enable us to learn about the shape of firms' costs.

The model leads to two forms of sorting in the equilibrium allocation of workers to jobs: (1) sorting by WTP given at any given level of productivity, and (2) sorting by productivity at any given level of WTP. The first implication cannot be used in practice since productivity is unobserved. The second implication can only be used in practice if it is possible to condition on individual-level WTP estimates.

While productivity is unobserved, we can make progress toward estimating the distribution of productivity with the following proposition: There is a monotonic relationship between worker productivity and the fraction of workers with the amenity; if the price of the amenity is higher, then the fraction of workers in jobs with the amenity is smaller, and vice versa. This assumption is supported by empirical observations in the literature, for example: (1) that "more- and less-educated workers are willing to give up the same fraction of earnings for different types of flexibility" even when the incidence of the amenity differs by education (Mas and Pallais, 2017), which is consistent with our pilot data; and (2) that it is difficult to predict which workers would volunteer to work from home in a Chinese firm even when ex-ante productivity is accounted for (Bloom et al., 2015). Under standard parametric assumptions about the distributions of unobserved productivity and the idiosyncratic error term, we can estimate the model using maximum likelihood (Flabbi and Moro, 2012; Hall and Mueller, 2018).

4.2 Tradeoffs between different amenities

Extending the model to the case that costs are independent across amenities is relatively straightforward. The challenge arises when the cost of providing one amenity may depend on whether the other amenity is present, i.e., there are complementarity or substitutability across amenities from the firms' perspective. Because complementarity and substitutability can also be present on the demand side when workers' values of individual amenities depend on the bundles they are considering, further assumptions are required to disentangle firms and workers' tradeoffs in equilibrium.

We assume that the cost of providing an amenity is monotonic in the worker's productivity π, and we allow for heterogeneity across firms in the form of cost shifters $f_j^1 \sim F^1$ and $f_j^2 \sim F^2$. The cost of providing amenities are given by $c_j(n_1, n_2; \pi) = (f_j^1 + k_{1,0}(\pi))n_1 + (f_j^2 + k_{0,1}(\pi))n_2 + k_{1,1}(\pi)n_1n_2$. Firms' rents are given by $p_A(\pi)n_1 + p_B(\pi)n_2 + p_{AB}(\pi)n_1n_2 - c_j(n_1, n_2; \pi)$. A given firm offers the amenity bundle (n_1, n_2) that maximizes their rent.

Worker i's utility function is $u = w + x_An_1 + x_Bn_2 + x_{AB}n_1n_2$, where x_A denotes the worker's WTP for n_1 when $n_2 = 0$, x_B denotes the worker's WTP for n_2 when $n_1 = 0$, $x_A + x_{AB}$ denotes the worker's WTP for n_1 when $n_2 = 1$, and $x_B + x_{AB}$ denotes the worker's WTP for n_2 when $n_1 = 1$. Workers' rents are given by $(x_A - p_A(\pi))n_1 + (x_B - p_B(\pi))n_2 + (x_{AB} - p_{AB}(\pi))n_1n_2$. All else equal, the worker prefers a job with the amenity bundle that maximizes their rent.

In this case, the amenity prices are denoted $p_A(\pi)$, $p_B(\pi)$, and $p_{AB}(\pi)$, with wage given by $w = \pi - p_A(\pi)n_1 - p_B(\pi)n_2 - p_{AB}(\pi)n_1n_2 + \epsilon$. Given the wage-setting equation above, we have $w_0 = \pi + \epsilon_{0,0}$, $w_A = \pi - p_A(\pi) + \epsilon_{1,0}$, $w_B = \pi - p_B(\pi) + \epsilon_{0,1}$, and $w_{AB} = \pi - p_A(\pi) - p_B(\pi) - p_{AB}(\pi) + \epsilon_{1,1}$.

In equilibrium, amenity prices satisfy a market-clearing condition: for all amenity bundles (n_1, n_2), the supply of jobs with that amenity bundle coincides with the demand for jobs with that amenity bundle.

Firms The firm chooses $(n_1, n_2) = (0, 0)$ if $f_A > p_A(\pi) - k_A(\pi)$, $f_B > p_B(\pi) - k_B(\pi)$, and $f_A + f_B > p_A(\pi) + p_B(\pi) + p_{AB}(\pi) - (k_A(\pi) + k_B(\pi) + k_{AB}(\pi))$. If $f_A \leq p_A(\pi) - k_A(\pi)$, then firm j is willing to provide amenity n_1. If $f_B \leq p_B(\pi) - k_B(\pi)$, then firm j is willing to provide amenity n_2. If $f_A + f_B \leq p_A(\pi) + p_B(\pi) + p_{AB}(\pi) - (k_A(\pi) + k_B(\pi) + k_{AB}(\pi))$, then firm j is willing to provide both amenities together.

Note that $A \preceq_j AB$ if and only if:

$$\begin{aligned} -(f_A + k_A(\pi)) + p_A(\pi) &\leq -(f_A + f_B + k_A(\pi) + k_B(\pi) + k_{AB}(\pi)) + p_A(\pi) + p_B(\pi) + p_{AB}(\pi) \\ \iff f_B &\leq (p_B(\pi) + p_{AB}(\pi)) - (k_B(\pi) + k_{AB}(\pi)) \end{aligned}$$

and $B \preceq_j AB$ if and only if:

$$\begin{aligned} -(f_B + k_B(\pi)) + p_B(\pi) &\leq -(f_A + f_B + k_A(\pi) + k_B(\pi) + k_{AB}(\pi)) + p_A(\pi) + p_B(\pi) + p_{AB}(\pi) \\ \iff f_A &\leq (p_A(\pi) + p_{AB}(\pi)) - (k_B(\pi) + k_{AB}(\pi)) \end{aligned}$$

and $A \preceq_j B$ if and only if:

$$\begin{aligned} -(f_A + k_A(\pi)) + p_A(\pi) &\leq -(f_B + k_B(\pi)) + p_B(\pi) \\ f_B - f_A &\leq (p_B(\pi) - p_A(\pi)) - (k_B(\pi) - k_A(\pi)) \end{aligned}$$

Thus, the firm provides AB if the following conditions hold:

$$\begin{aligned} f_A + f_B &\leq (p_A(\pi) + p_B(\pi) + p_{AB}(\pi)) - (k_A(\pi) + k_B(\pi) + k_{AB}(\pi)) \\ f_B &\leq (p_B(\pi) + p_{AB}(\pi)) - (k_B(\pi) + k_{AB}(\pi)) \\ f_A &\leq (p_A(\pi) + p_{AB}(\pi)) - (k_A(\pi) + k_{AB}(\pi)) \end{aligned}$$

The firm provides A if the following conditions hold:

$$\begin{aligned} f_A &\leq p_A(\pi) - k_A(\pi) \\ f_B &> (p_B(\pi) + p_{AB}(\pi)) - (k_B(\pi) + k_{AB}(\pi)) \\ f_B - f_A &> (p_B(\pi) - p_A(\pi)) - (k_B(\pi) - k_A(\pi)) \end{aligned}$$

And the firm provides B if the following conditions hold:

$$\begin{aligned} f_B &\leq p_B(\pi) - k_B(\pi) \\ f_A &> (p_A(\pi) + p_{AB}(\pi)) - (k_B(\pi) + k_{AB}(\pi)) \\ f_B - f_A &\leq (p_B(\pi) - p_A(\pi)) - (k_B(\pi) - k_A(\pi)) \end{aligned}$$

Workers Define the worker's rent as $\rho_i^{n_1,n_2}(\pi) = x_{n_1,n_2} - p_{n_1,n_2}(\pi)$. In particular:

$$\begin{aligned}
&\rho_i^{1,0}(\pi) = x_A - p_A(\pi)\\
&\rho_i^{0,1}(\pi) = x_A - p_B(\pi)\\
&\rho_i^{1,1}(\pi) = x_A + x_B + x_{AB} - p_A(\pi) - p_B(\pi) - p_{AB}(\pi)
\end{aligned}$$

The worker chooses $(n_1, n_2) = (0, 0)$ if $p_A(\pi) > x_A$, $p_B(\pi) > x_B$, and $p_A(\pi) + p_B(\pi) + p_{AB}(\pi) > x_A + x_B + x_{AB}$. If $x_A \geq p_A(\pi)$, then worker i is willing to accept amenity n_1. If $x_B \geq p_B(\pi)$, then worker i is willing to accept amenity n_2. If $x_A + x_B + x_{AB} \geq p_A(\pi) + p_B(\pi) + p_{AB}(\pi)$, then worker i is willing to accept both amenities together.

Note that $A \preceq_i AB$ if and only if:

$$\begin{aligned}
&x_A - p_A(\pi) \leq x_A + x_B + x_{AB} - p_A(\pi) - p_B(\pi) - p_{AB}(\pi)\\
\iff\ & p_B(\pi) + p_{AB}(\pi) \leq x_B + x_{AB}
\end{aligned}$$

$B \preceq_i AB$ if and only if:

$$\begin{aligned}
&x_B - p_B(\pi) \leq x_A + x_B + x_{AB} - p_A(\pi) - p_B(\pi) - p_{AB}(\pi)\\
\iff\ & p_A(\pi) + p_{AB}(\pi) \leq x_A + x_{AB}
\end{aligned}$$

$A \preceq_i B$ if and only if:

$$\begin{aligned}
&x_A - p_A(\pi) \leq x_B - p_B(\pi)\\
\iff\ & p_B(\pi) - p_A(\pi) \leq x_B - x_A
\end{aligned}$$

Thus, the worker demands AB if the following conditions hold:

$$\begin{aligned}
x_A + x_B + x_{AB} &\geq p_A(\pi) + p_B(\pi) + p_{AB}(\pi)\\
x_B + x_{AB} &\geq p_B(\pi) + p_{AB}(\pi)\\
x_A + x_{AB} &\geq p_A(\pi) + p_{AB}(\pi)
\end{aligned}$$

The worker demands A if the following conditions hold:

$$x_A \geq p_A(\pi)$$
$$x_B + x_{AB} < p_B(\pi) + p_{AB}(\pi)$$
$$x_B - x_A < p_B(\pi) - p_A(\pi)$$

And the worker demands B if the following conditions hold:

$$x_B \geq p_B(\pi)$$
$$x_A + x_{AB} < p_A(\pi) + p_{AB}(\pi)$$
$$x_B - x_A \geq p_B(\pi) - p_A(\pi)$$

For a visual illustration of the equilibrium in this model, see Figure 21 for the case of a positive price interaction and Figure 22 for the case of a negative price interaction.

5 Estimation and Results

We leverage the joint distribution between wages and willingness-to-pay for amenities to estimate the model.

5.1 One amenity

5.1.1 Parametrization

We have $w_i = \pi_i - n_i p(\pi_i)$: wage is productivity net of amenity price if one has the amenity. Amenity price $p(\pi_i)$ is a function of one's productivity.

Let $\pi_i \equiv \mu_i + \epsilon_i = \gamma Z_i + \epsilon_i$ be the productivity of person i with observable characteristics Z_i and unobserved component ϵ_i.

Let $p(\pi) = \alpha + \beta\pi$ the amenity pricing function given productivity level π. This linear form can be relaxed in the future.

We assume that WTPs are measured with a random error term u, i.e., true WTP $x = \tilde{x} - u$, with $\tilde{x}$ our measured WTP.

Assume $u \sim \mathcal{N}(0, \sigma_u)$ and $\epsilon \sim \mathcal{N}(0, \sigma_\epsilon)$ independent of each other. Note that if we work in wage (dollar) unit instead of in log wage unit, then we should perhaps assume that $\log(u) \sim \mathcal{N}(0, \sigma_u)$ and $\log(\epsilon) \sim \mathcal{N}(0, \sigma_\epsilon)$.

Let θ be the parameter vector, consisting α, β, and elements of the vector γ, we are interested in finding $\hat{\theta}$ to maximize the log likelihood: $\hat{\theta} = \arg\max_\theta \sum_i \log \Pr(w_i, n_i \,|\, \tilde{x}, \theta)$.

5.1.2 Likelihood

To facilitate writing down this likelihood function, we will write $\Pr(w_i, n_i \,|\, \tilde{x}, \theta) = \Pr(n_i \,|\, \tilde{x}, \theta) \cdot \Pr(w_i \,|\, n_i, \tilde{x}, \theta)$.

Consider the first piece, $\Pr(n_i \,|\, \tilde{x}, \theta)$. Assume u_i is known, then

$$\Pr(n_i = 0 \,|\, \tilde{x}, \theta, u_i) = \Pr_\epsilon(\tilde{x} - u_i < \alpha + \beta(\mu_i + \epsilon_i))$$
$$\Pr(n_i = 1 \,|\, \tilde{x}, \theta, u_i) = \Pr_\epsilon(\tilde{x} - u_i > \alpha + \beta(\mu_i + \epsilon_i))$$

The reason that we fix u_i here is because, the two pieces should share the same u_i if it needs to appear in both pieces. If we need to integrate out u_i, we should do that after getting the joint likelihood for person i.

Consider the second piece $\Pr(w_i \,|\, n_i, \tilde{x}, \theta, u_i)$.

If $n_i = 0$, then we want to know the density of $\mu_i + \epsilon_i \sim \mathcal{N}(\mu_i, \sigma_\epsilon)$ evaluated at the data point w_i, given that this density is appropriately truncated such that $\tilde{x} - u_i < \alpha + \beta(\mu_i + \epsilon_i)$. This means, this density is 0 if $\tilde{x} - u_i > \alpha + \beta(\mu_i + \epsilon_i) = \alpha + \beta w_i$. The truncation also means that we need to divide by $\Pr_\epsilon(\tilde{x} - u_i < \alpha + \beta(\mu_i + \epsilon_i))$.

Therefore, in this case:

$$\Pr(w_i \,|\, n_i = 0, \tilde{x}, \theta, u_i) = \frac{\phi(w_i, \mu_i, \sigma_\epsilon) \cdot \mathbf{1}_{\{\tilde{x} - u_i < \alpha + \beta w_i\}}}{\Pr_\epsilon(\tilde{x} - u_i < \alpha + \beta(\mu_i + \epsilon_i))}$$

Here, we denote $\phi(z, \mu, \sigma)$ as the normal PDF with mean μ, standard deviation σ, evaluated at z.

If $n_i = 1$, then we want to know the density of $\mu_i + \epsilon_i - (\alpha + \beta(\mu_i + \epsilon_i)) \sim$

$\mathcal{N}(\mu_i - (\alpha + \beta\mu_i), |1-\beta|\sigma_\epsilon)$ evaluated at the data point w_i, given that this density is appropriately truncated such that $\tilde{x} - u_i > \alpha + \beta(\mu_i + \epsilon_i)$. This density is 0 if $\tilde{x} - u_i > \alpha + \beta\pi_i = \alpha + \beta\frac{w+\alpha}{1-\beta}$. The last equality is because $w_i = \pi_i - (\alpha + \beta\pi_i)$ with $n = 1$. The truncation also means that we need to divide by $\Pr_\epsilon(\tilde{x} - u_i > \alpha + \beta(\mu_i + \epsilon_i))$.

Therefore, in this case:

$$\Pr(w_i \,|\, n_i = 1, \tilde{x}, \theta, u_i) = \frac{\phi(w_i, \mu_i - (\alpha + \beta\mu_i), |1-\beta|\sigma_\epsilon) \cdot \mathbf{1}_{\left\{\tilde{x} - u_i > \alpha + \beta\frac{w+\alpha}{1-\beta}\right\}}}{\Pr_\epsilon(\tilde{x} - u_i > \alpha + \beta(\mu_i + \epsilon_i))}$$

Now we can combine the two pieces, noting the cancellation.

If u_i is observed, then

$$\begin{aligned}
\Pr(w_i, n_i = 0 \,|\, \tilde{x}, \theta, u_i) &= \phi(w_i, \mu_i, \sigma_\epsilon) \cdot \mathbf{1}_{\{\tilde{x} - u_i < \alpha + \beta w_i\}} \\
\Pr(w_i, n_i = 1 \,|\, \tilde{x}, \theta, u_i) &= \phi(w_i, \mu_i - (\alpha + \beta\mu_i), |1-\beta|\sigma_\epsilon) \cdot \mathbf{1}_{\left\{\tilde{x} - u_i > \alpha + \beta\frac{w+\alpha}{1-\beta}\right\}}
\end{aligned}$$

Because u_i is actually unobserved, we need to integrate it out. Note that u_i only appears in the indicator term. Therefore,

$$\begin{aligned}
\Pr(w_i, n_i = 0 \,|\, \tilde{x}, \theta) &= \phi(w_i, \mu_i, \sigma_\epsilon) \cdot \Pr_u[u_i > \tilde{x} - (\alpha + \beta w_i)] \\
&= \phi(w_i, \mu_i, \sigma_\epsilon)[1 - \Phi(\tilde{x} - (\alpha + \beta w_i), 0, \sigma_u)] \\
\Pr(w_i, n_i = 1 \,|\, \tilde{x}, \theta) &= \phi(w_i, \mu_i - (\alpha + \beta\mu_i), |1-\beta|\sigma_\epsilon) \cdot \Pr_u\left[u_i < \tilde{x} - \left(\alpha + \beta\frac{w+\alpha}{1-\beta}\right)\right] \\
&= \phi(w_i, \mu_i - (\alpha + \beta\mu_i), |1-\beta|\sigma_\epsilon)\Phi\left(\tilde{x} - \left(\alpha + \beta\frac{w+\alpha}{1-\beta}, 0, \sigma_u\right)\right)
\end{aligned}$$

Here, we denote $\Phi(z, \mu, \sigma)$ as the normal CDF with mean μ, standard deviation σ, evaluated at z.

We then estimate the model using maximum likelihood.

5.2 Tradeoffs between different amenities

5.2.1 Parametrization

We have $w_i = \pi_i - n_i^A p^A(\pi_i) - n_i^B p^B(\pi_i) - n_i^A n_i^B p^{AB}(\pi_i)$: wage is productivity net of amenity price if one has the amenity. There are two amenities here, A, and B, each with its own pricing function p^A and p^B. If a person has both amenities, they also have to pay p^{AB}.

Let $\pi_i \equiv \mu_i + \epsilon_i = \gamma Z_i + \epsilon_i$ be the productivity of person i with observable characteristics Z_i and unobserved component ϵ_i.

Let $p^A(\pi) = \alpha^A + \beta^A \pi$ the amenity pricing function for amenity A given productivity level π. Let $p^B(\pi) = \alpha^B + \beta^B \pi$ the amenity pricing function for amenity B given productivity level π. Let $p^{AB}(\pi) = \alpha^{AB} + \beta^{AB}\pi$ the amenity pricing function for the additional (could be negative) price for having both A and B given productivity level π.

We assume that WTPs are measured with random error terms:

$$\begin{aligned} x^A &= \tilde{x}^A - u^A \\ x^B &= \tilde{x}^B - u^B \\ x^{AB} &= \tilde{x}^{AB} - u^{AB} \end{aligned}$$

with x^A measured WTP for amenity A, x^B for amenity B, x^{AB} additional (can be negative) WTP for having both.

Assume $u^A \sim \mathcal{N}\left(0, \sigma_u^A\right)$, $u^B \sim \mathcal{N}\left(0, \sigma_u^B\right)$, $u^{AB} \sim \mathcal{N}\left(0, \sigma_u^{AB}\right)$, $\epsilon \sim \mathcal{N}(0, \sigma_\epsilon)$, all independent of each other.

Let θ be the parameter vector, consisting α^A, β^A, α^B, β^B, α^{AB}, β^{AB}, and elements of the vector γ, we are interested in finding $\hat{\theta}$ to maximize the log likelihood: $\hat{\theta} = \arg\max_\theta \sum_i \log \Pr\left(w_i, n_i^A, n_i^B \,\middle|\, \tilde{x}_i^A, \tilde{x}_i^B, \tilde{x}_i^{AB}, \theta\right)$.

5.2.2 Likelihood

Following the same steps as above: Consider u_i^A, u_i^B, u_i^{AB} as known.

If $n_i^A = 0$ and $n_i^B = 0$ then $w_i = \mu_i + \epsilon_i \sim \mathcal{N}(\mu_i, \sigma_\epsilon)$ and $\pi_i = w_i$.

$$\Pr\Big(w_i, n_i^A = 0, n_i^B = 0 \,\Big|\, \theta, \tilde{x}_i\text{'s}, u_i\text{'s}\Big) = \phi(w_i, \mu_i, \sigma_\epsilon) \cdot \mathbf{1}_{\left\{\tilde{x}_i^A - u_i^A < \alpha^A + \beta^A w_i\right\}} \cdot \mathbf{1}_{\left\{\tilde{x}_i^B - u_i^B < \alpha^B + \beta^B w_i\right\}} \cdot \mathbf{1}_{\left\{\tilde{x}_i^A - u_i^A + \tilde{x}_i^B - u_i^B + \tilde{x}_i^{AB} - u_i^{AB} < \alpha^A + \alpha^B + \alpha^{AB} + (\beta^A + \beta^B + \beta^{AB}) w_i\right\}}$$

If $n_i^A = 0$ and $n_i^B = 1$ then $w_i = \mu_i + \epsilon_i - (\alpha^B + \beta^B \mu_i + \beta^B \epsilon_i) \sim \mathcal{N}\Big(\mu_i - (\alpha^B + \beta^B \mu_i, \Big|1 - \beta^B\Big|\sigma_\epsilon\Big)$ and $\pi_i = \frac{w_i + \alpha^B}{1 - \beta^B}$.

$$\Pr\Big(w_i, n_i^A = 0, n_i^B = 1 \,\Big|\, \theta, \tilde{x}_i\text{'s}, u_i\text{'s}\Big) = \phi(w_i, \mu_i - (\alpha^B + \beta^B \mu_i), \Big|1 - \beta^B\Big|\sigma_\epsilon) \cdot \mathbf{1}_{\left\{(\tilde{x}_i^B - u_i^B) - (\tilde{x}_i^A - u_i^A) > (\alpha^B - \alpha^A) + (\beta^B - \beta^A)\frac{w_i + \alpha^B}{1 - \beta^B}\right\}} \cdot \mathbf{1}_{\left\{\tilde{x}_i^B - u_i^B > \alpha^B + \beta^B \frac{w_i + \alpha^B}{1 - \beta^B}\right\}} \cdot \mathbf{1}_{\left\{\tilde{x}_i^A - u_i^A + \tilde{x}_i^{AB} - u_i^{AB} < \alpha^A + \alpha^{AB} + (\beta^A + \beta^{AB})\frac{w_i + \alpha^B}{1 - \beta^B}\right\}}$$

If $n_i^A = 1$ and $n_i^B = 0$ then $w_i = \mu_i + \epsilon_i - (\alpha^A + \beta^A \mu_i + \beta^A \epsilon_i) \sim \mathcal{N}\Big(\mu_i - (\alpha^A + \beta^A \mu_i, \Big|1 - \beta^A\Big|\sigma_\epsilon\Big)$ and $\pi_i = \frac{w_i + \alpha^A}{1 - \beta^A}$.

$$\Pr\Big(w_i, n_i^A = 1, n_i^B = 0 \,\Big|\, \theta, \tilde{x}_i\text{'s}, u_i\text{'s}\Big) = \phi(w_i, \mu_i - (\alpha^A + \beta^A \mu_i), \Big|1 - \beta^A\Big|\sigma_\epsilon) \cdot \mathbf{1}_{\left\{\tilde{x}_i^A - u_i^A > \alpha^A + \beta^A \frac{w_i + \alpha^A}{1 - \beta^A}\right\}} \cdot \mathbf{1}_{\left\{(\tilde{x}_i^A - u_i^A) - (\tilde{x}_i^B - u_i^B) > (\alpha^A - \alpha^B) + (\beta^A - \beta^B)\frac{w_i + \alpha^A}{1 - \beta^A}\right\}} \cdot \mathbf{1}_{\left\{\tilde{x}_i^B - u_i^B + \tilde{x}_i^{AB} - u_i^{AB} < \alpha^B + \alpha^{AB} + (\beta^B + \beta^{AB})\frac{w_i + \alpha^A}{1 - \beta^A}\right\}}$$

If $n_i^A = 1$ and $n_i^B = 1$ then $w_i = \mu_i + \epsilon_i - (\alpha^A + \beta^A \mu_i + \beta^A \epsilon_i) - (\alpha^B + \beta^B \mu_i + \beta^B \epsilon_i) - (\alpha^{AB} + \beta^{AB} \mu_i + \beta^{AB} \epsilon_i) \sim \mathcal{N}\Big(\mu_i - (\alpha^A + \alpha^B + \alpha^{AB} + (\beta^A + \beta^B + \beta^{AB})\mu_i), \Big|1 - \beta^A - \beta^B - \beta^{AB}\Big|\sigma_\epsilon\Big)$

and $\pi_i = \frac{w_i+\alpha^A+\alpha^B+\alpha AB}{1-\beta^A-\beta^B-\beta^{AB}}$.

$$\begin{aligned}
\Pr\Big(w_i, n_i^A = 0, n_i^B = 0 \,\Big|\, \theta, \tilde{x}_i\text{'s}, u_i\text{'s}\Big) = \phi(w_i, \mu_i - (\alpha^A + \alpha^B + \alpha^{AB} + (\beta^A + \beta^B + \beta^{AB})\mu_i), \Big|1 - \beta^A - \beta^B \\
\cdot \mathbf{1}_{\left\{\tilde{x}_i^A - u_i^A + \tilde{x}_i^{AB} - u_i^{AB} > (\alpha^A + \alpha^{AB}) + (\beta^A + \beta^{AB}) \frac{w_i+\alpha^A+\alpha^B+\alpha AB}{1-\beta^A-\beta^B-\beta^{AB}}\right\}} \\
\cdot \mathbf{1}_{\left\{\tilde{x}_i^B - u_i^B + \tilde{x}_i^{AB} - u_i^{AB} > (\alpha^B + \alpha^{AB}) + (\beta^B + \beta^{AB}) \frac{w_i+\alpha^A+\alpha^B+\alpha AB}{1-\beta^A-\beta^B-\beta^{AB}}\right\}} \\
\cdot \mathbf{1}_{\left\{\tilde{x}_i^A - u_i^A + \tilde{x}_i^B - u_i^B + \tilde{x}_i^{AB} - u_i^{AB} > \alpha^A + \alpha^B + \alpha^{AB} + (\beta^A + \beta^B + \beta^{AB}) \frac{w_i+\alpha^A+\alpha^B+\alpha AB}{1-\beta^A-\beta^B-\beta^{AB}}\right\}}
\end{aligned}$$

To find $\Pr\Big(w_i, n_i^A, n_i^B \,\Big|\, \theta, \tilde{x}_i\text{'s}\Big)$, we would then integrate the indicator terms above over the u_i^A, u_i^B, and u_i^{AB}.

5.3 Results

The model can rationalize important patterns in the data. In Table 4, the model fits the distribution of wages, the presence of the amenity, and the distribution of utility well. More importantly, the model fits the relationship between wages and amenity, wages and willingness-to-pay, as well as amenity and willingness-to-pay. There is strong sorting by willingness to pay, and high-wage workers are more likely to have the amenity than low-wage workers.

In one counterfactual, we eliminate heterogeneity in cost by productivity by flattening out $p(\pi)$ at the price that would arise if everyone sorted perfectly by WTP. This results in better sorting by WTP, with higher-wage workers now tend to be those without the amenity due to compensating differentials. Even then, we see 6% decrease in wage dispersion and 8% decrease in utility dispersion, despite average wages remaining unchanged. The results suggest an important role for changes in technology or how jobs are structured in shaping income inequality (Goldin, 2014).

6 Conclusion

This paper studies the interplay between how much workers value workplace flexibility, whether they have such amenities, and how the presence of amenities affects their wages. Even within firms, workers differ in the benefits they receive. In a survey of over 30,000 workers, Barrero, Bloom and Davis (2021) document that workers desire workplace flexibility more than what firms provide, on average, and moreover, the gap is much larger at the lower end of the earnings distribution. Inequality is exacerbated when "good amenities" go to high-earning workers rather than those who desire them most. The pandemic has further highlighted the unequal distribution of workplace flexibility.

Collecting new data of individual workers' job details including their work arrangements and wages, together with quantitative measures of their willingness to pay (WTP) for different forms of workplace flexibility. Capturing how much workers are willing to forgo in wages to trade off having more workplace flexibility at such a fine level is a technical challenge we overcome by developing a novel dynamic elicitation tool.

The project examines a new model of compensating differentials (Rosen, 1986) in which workers face different "prices" of workplace flexibility. The model provides a novel explanation for why high wages often go with "good" amenities, even in a compensating differential framework: high-wage workers face a lower wage penalty to obtain amenities, independent of their WTP.

Workplace flexibility has been the subject of an ongoing policy debate as to the role of the government in promoting work arrangements that facilitate work-life balance, as reflected in reports from the Council of Economic Advisors (2010, 2014). Combining our model of firms' costs with the full distribution of workers' preferences therefore fully characterizes the labor market equilibrium, which enables us to estimate a structural model to evaluate policy counterfactuals and measure welfare. We further estimate the model using the new data to explore how equalizing firms' costs of providing workplace flexibility (e.g., with technological investment) may have the potential to realign workers with their desired workplace flexibility across the income distribution and to explore the impact of such changes on the structure of wages and welfare.

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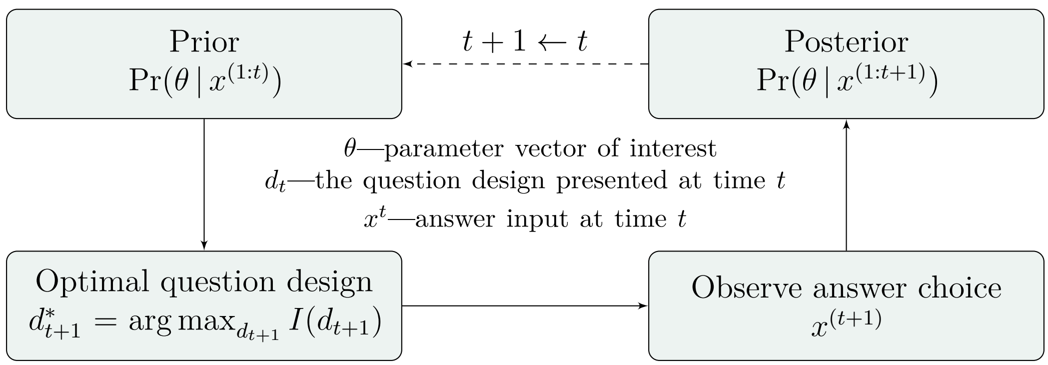
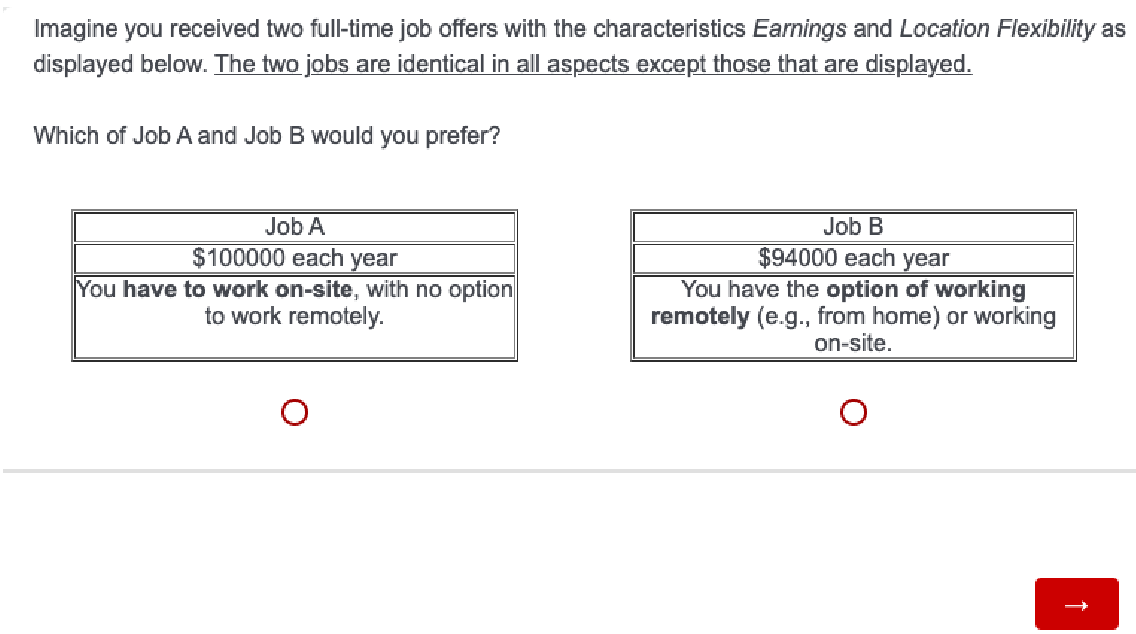
Figure 1: Adaptive Bayesian selection procedure of discrete choice scenarios



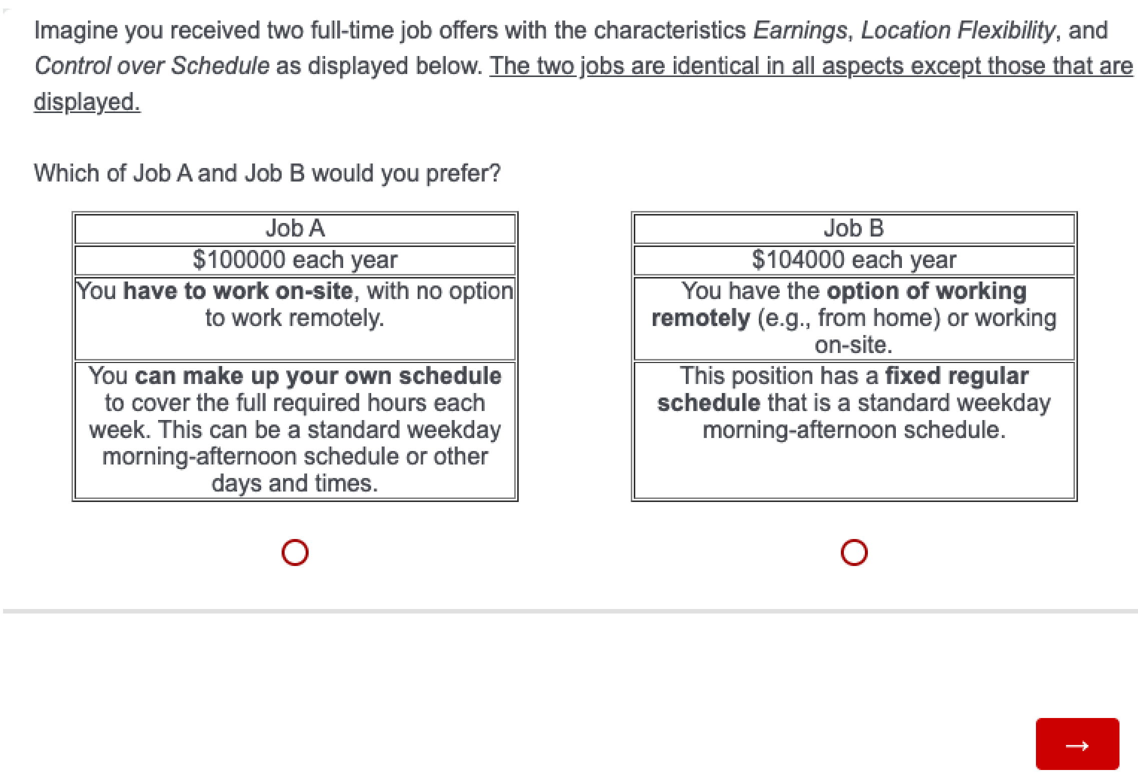
Note: See Section 2.1 for the notation. The initial prior for the parameter vector θ, initialized at $t = 0$, can be a uniform prior over the parameter space or chosen according to a pilot experiment. The Bayesian adaptive procedure chooses the question design that maximizes the *mutual information* between the parameter random value Θ and the outcome random value $X^{(t+1)}$, i.e., $I(d_{t+1}) \coloneqq I\big(\Theta; X^{t+1}|d_{t+1}\big)$, and then updates with the respondent's answer choice to the chosen question. The new data are used to update the posterior of θ using Bayes' rule, $\Pr\big(\theta \,\big|\, x^{(1:t+1)}, d_{t+1}\big) = \frac{\Pr\left(x^{t+1} \,\middle|\, \theta, d_{t+1}\right) \Pr\left(\theta \,\middle|\, x^{(1:t)}\right)}{\int_{\theta'} \Pr(x^{t+1} \mid \theta', d_{t+1}) \Pr\left(\theta' \,\middle|\, x^{(1:t)}\right) d\theta'}$, and the updated posterior is used as the prior in the next round.

Figure 2: Example of hypothetical scenario with one amenity



Note: See Table 2 for the definitions of the job characteristics considered.

Figure 3: Example of hypothetical scenario with two amenities



Imagine you received two full-time job offers with the characteristics *Earnings*, *Location Flexibility*, and *Control over Schedule* as displayed below. The two jobs are identical in all aspects except those that are displayed.

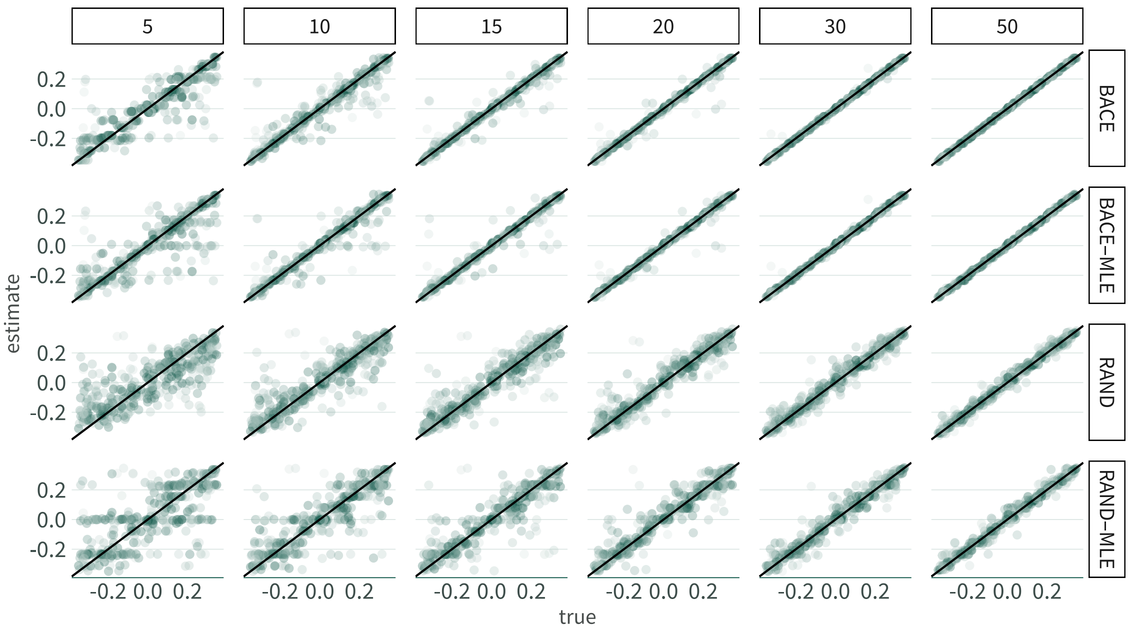
Which of Job A and Job B would you prefer?

Job A	Job B
$100000 each year	$104000 each year
You **have to work on-site**, with no option to work remotely.	You have the **option of working remotely** (e.g., from home) or working on-site.
You **can make up your own schedule** to cover the full required hours each week. This can be a standard weekday morning-afternoon schedule or other days and times.	This position has a **fixed regular schedule** that is a standard weekday morning-afternoon schedule.

→

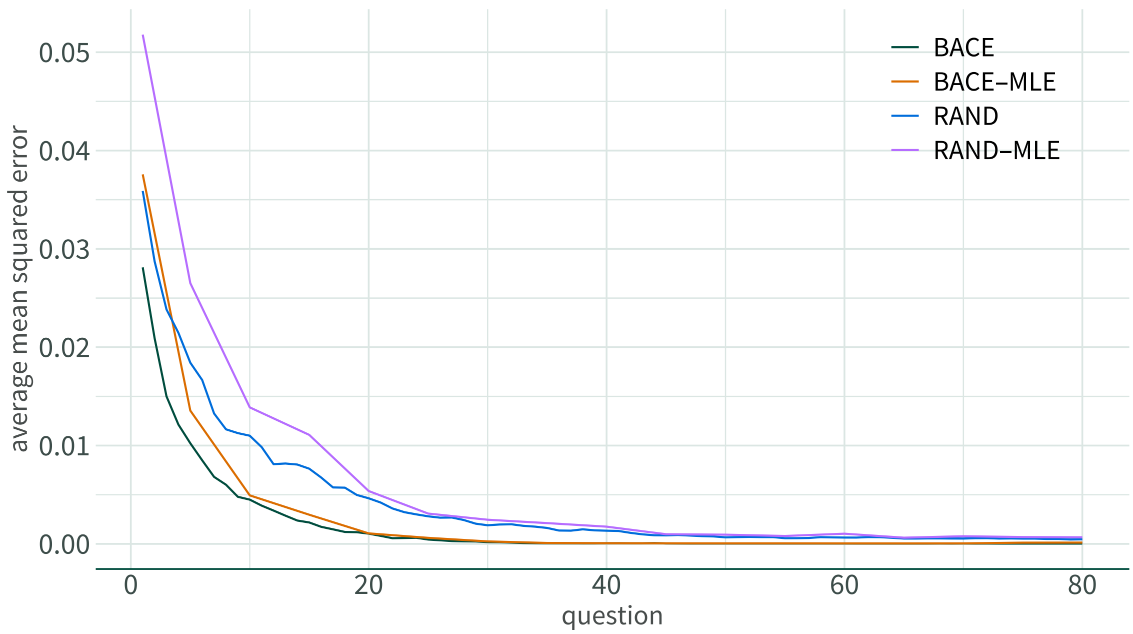
Note: See Table 2 for the definitions of the job characteristics considered.

Figure 4: Recovering amenity value coefficient when one amenity is presented



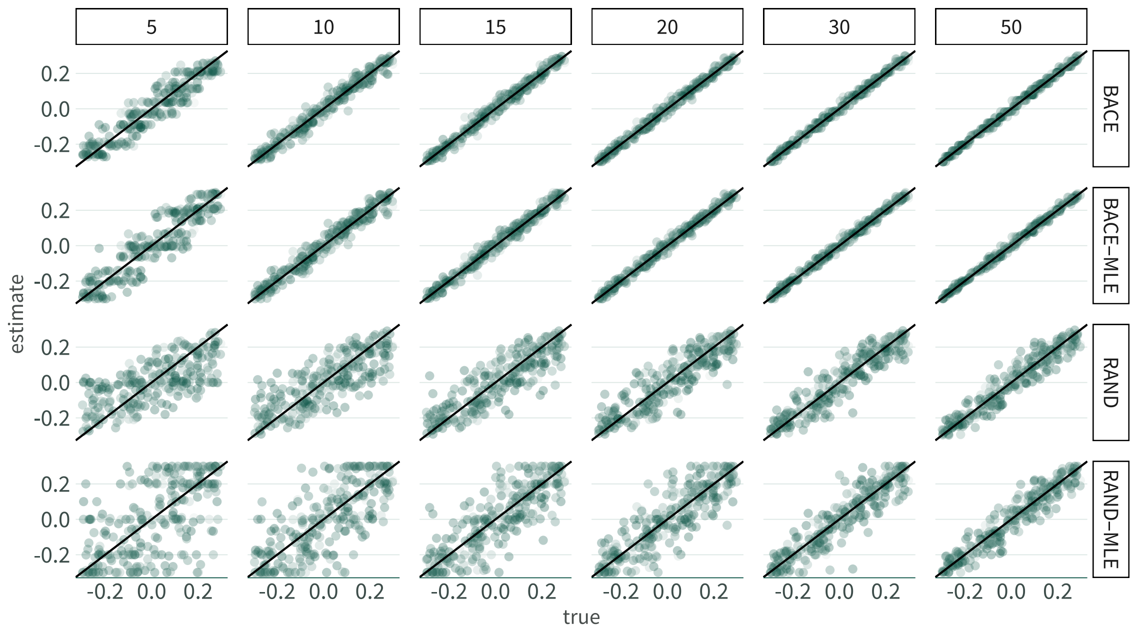
Note: The figure depicts the simulation results in the case when a binary choice is presented between two jobs which differ along two dimensions: earnings and the presence or absence of one amenity. The y-axis is the true parameter value on the amenity coefficient.
The x-axis is the estimated parameter value on the amenity coefficient using four methods: when the sequence of questions are generated by the Bayesian Adaptive Choice Experiment (BACE) or randomly (RAND), and when the coefficients are recovered using the Bayesian approach or using a maximum likelihood estimator (MLE).
The lighter color corresponds to higher value of true p, the parameter that corresponds to the probability of choosing randomly rather than choosing the choice with higher utility.
Rows are the four methods (see above).
Columns are the estimates after the number of questions asked.

Figure 5: Average mean squared error between true and estimated amenity value coefficients when one amenity is presented



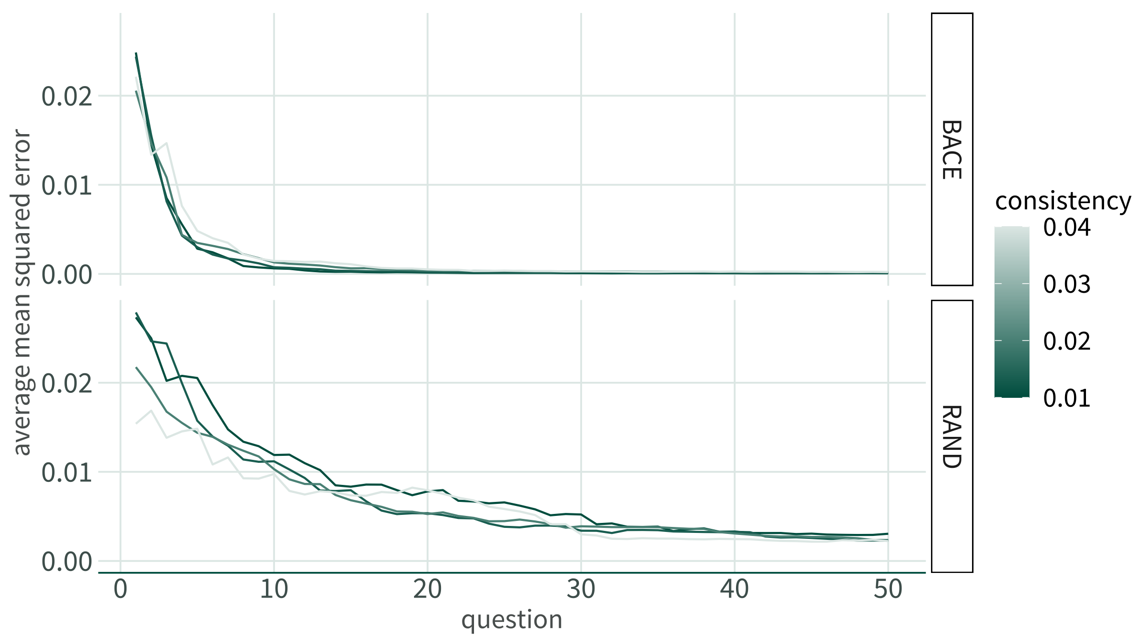
Note: The figure depicts the simulation results in the case when a binary choice is presented between two jobs which differ along two dimensions: earnings and the presence or absence of one amenity. The x-axis is the number of questions used to obtain amenity coefficient estimates.
The y-axis is the average mean squared error between the estimates and the true values from the simulations.
The colors map to four methods: when the sequence of questions are generated by the Bayesian Adaptive Choice Experiment (BACE) or randomly (RAND), and when the coefficients are recovered using the Bayesian approach or using a maximum likelihood estimator (MLE).

Figure 6: Recovering first amenity value coefficient when two amenities are presented



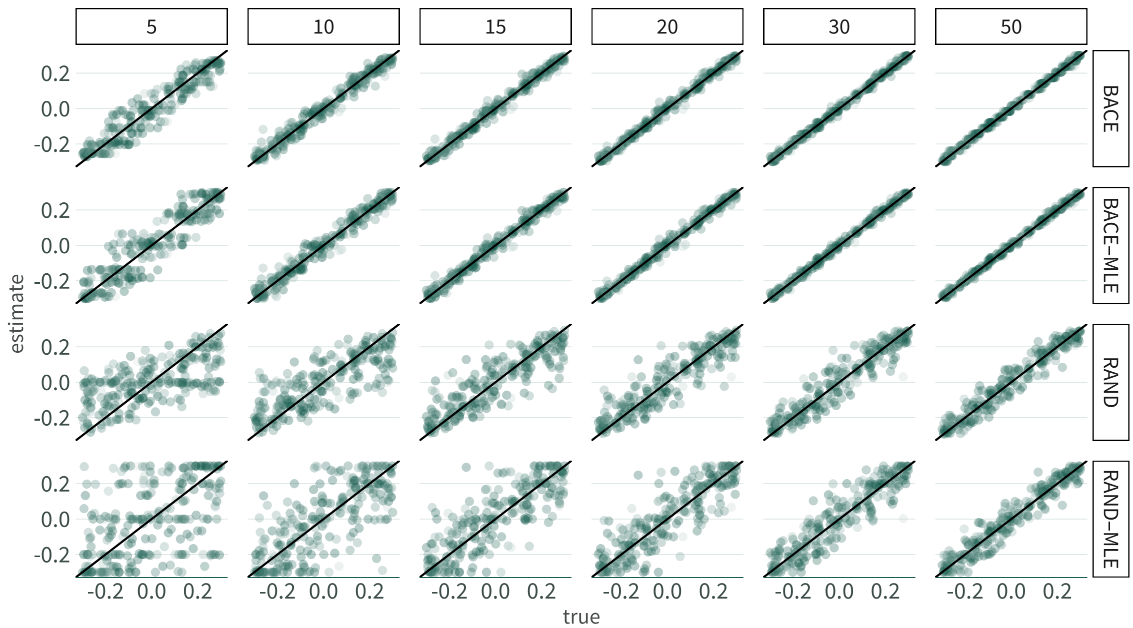
Note: The figure depicts the simulation results in the case when a binary choice is presented between two jobs which differ along three dimensions: earnings and the presence or absence of each of two amenities.
The y-axis is the true parameter value on the first amenity coefficient.
The x-axis is the estimated parameter value on the first amenity coefficient using four methods: when the sequence of questions are generated by the Bayesian Adaptive Choice Experiment (BACE) or randomly (RAND), and when the coefficients are recovered using the Bayesian approach or using a maximum likelihood estimator (MLE).
The lighter color corresponds to higher value of true p, the parameter that corresponds to the probability of choosing randomly rather than choosing the choice with higher utility.
Rows are the four methods (see above).
Columns are the estimates after the number of questions asked.

Figure 7: Average mean squared error between true and estimated first amenity value coefficients when two amenities are presented



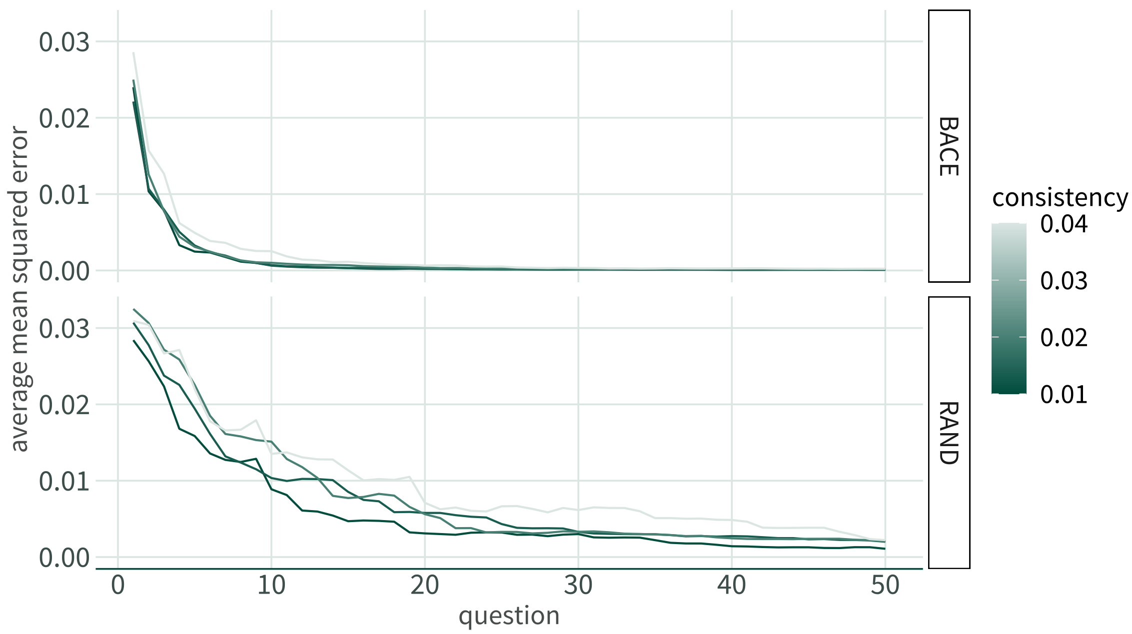
Note: The figure depicts the simulation results in the case when a binary choice is presented between two jobs which differ along three dimensions: earnings and the presence or absence of each of two amenities.
The x-axis is the number of questions used to obtain amenity coefficient estimates.
The y-axis is the average mean squared error between the estimates and the true values from the simulations.
The panels map to two methods: when the sequence of questions are generated by the Bayesian Adaptive Choice Experiment (BACE) or randomly (RAND). The colors correspond to different values of the choice inconsistency parameter.

Figure 8: Recovering second amenity value coefficient when two amenities are presented



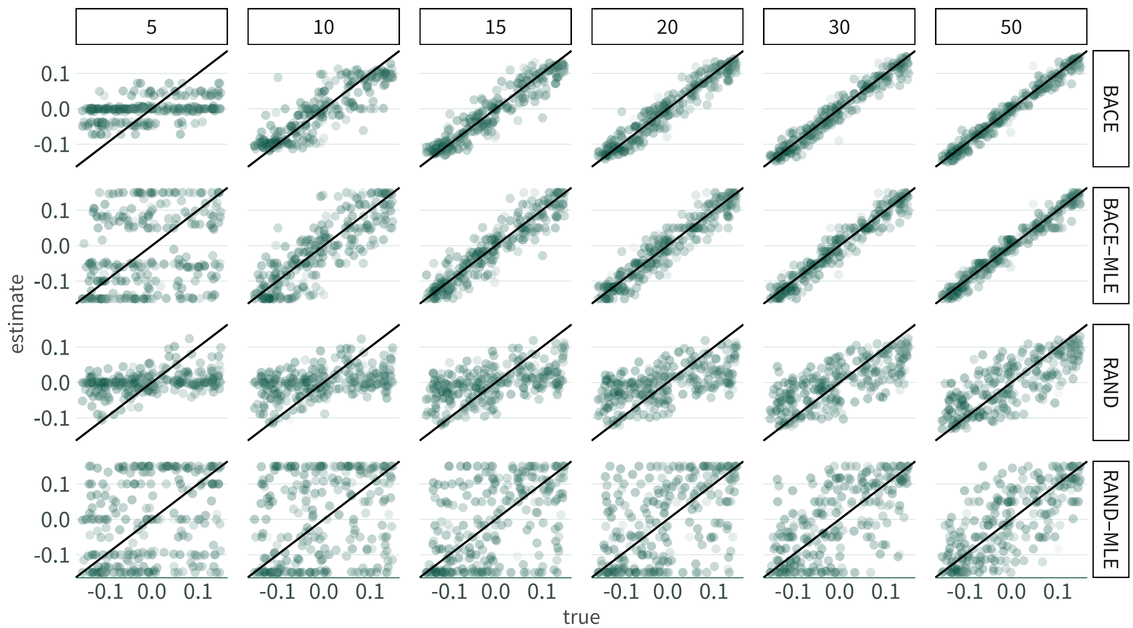
Note: The figure depicts the simulation results in the case when a binary choice is presented between two jobs which differ along three dimensions: earnings and the presence or absence of each of two amenities.
The y-axis is the true parameter value on the second amenity coefficient.
The x-axis is the estimated parameter value on the second amenity coefficient using four methods: when the sequence of questions are generated by the Bayesian Adaptive Choice Experiment (BACE) or randomly (RAND), and when the coefficients are recovered using the Bayesian approach or using a maximum likelihood estimator (MLE).
The lighter color corresponds to higher value of true p, the parameter that corresponds to the probability of choosing randomly rather than choosing the choice with higher utility.
Rows are the four methods (see above).
Columns are the estimates after the number of questions asked.

Figure 9: Average mean squared error between true and estimated second amenity value coefficients when two amenities are presented



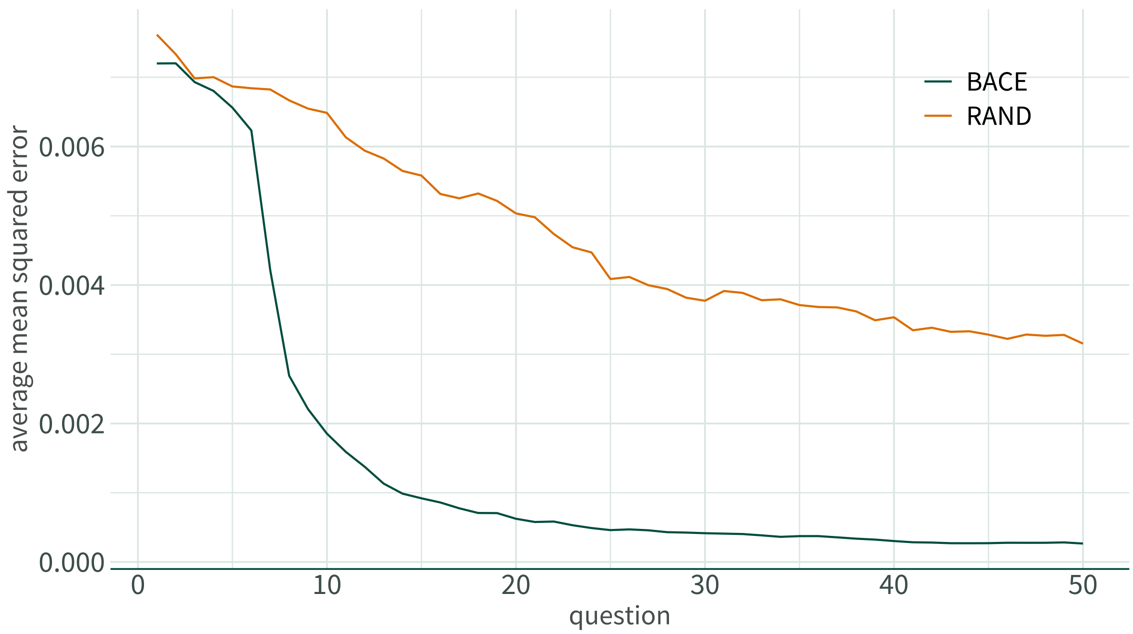
Note: The figure depicts the simulation results in the case when a binary choice is presented between two jobs which differ along three dimensions: earnings and the presence or absence of each of two amenities.
The x-axis is the number of questions used to obtain amenity coefficient estimates.
The y-axis is the average mean squared error between the estimates and the true values from the simulations.
The panels map to two methods: when the sequence of questions are generated by the Bayesian Adaptive Choice Experiment (BACE) or randomly (RAND). The colors correspond to different values of the choice inconsistency parameter.

Figure 10: Recovering the interaction coefficient when two amenities are presented



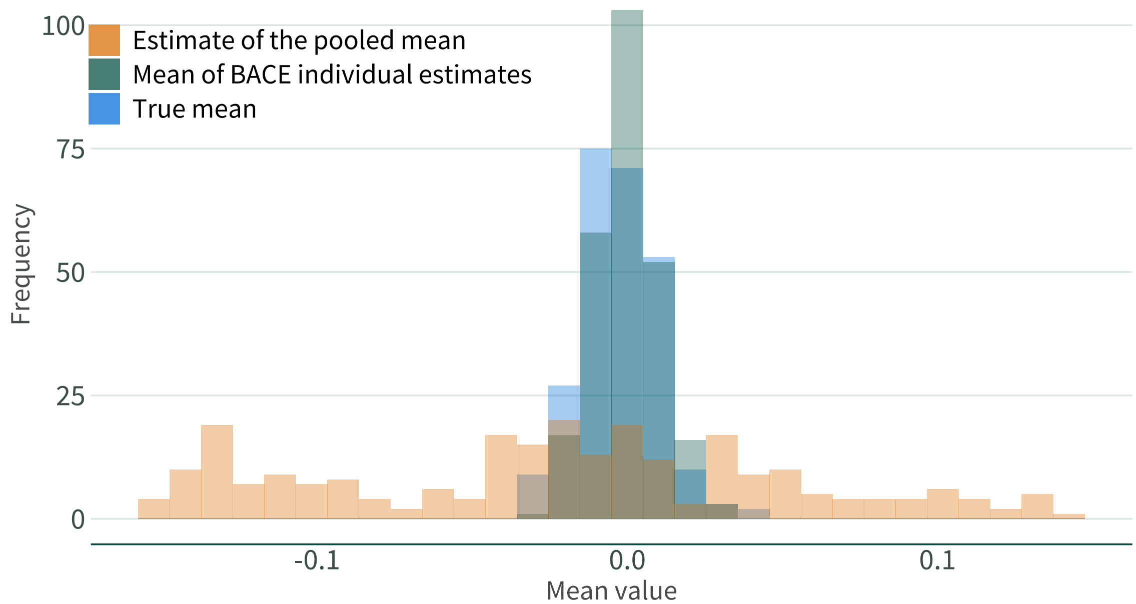
Note: The figure depicts the simulation results in the case when a binary choice is presented between two jobs which differ along three dimensions: earnings and the presence or absence of each of two amenities.
The y-axis is the true parameter value on the interaction term between the two amenities.
The x-axis is the estimated interaction coefficient using four methods: when the sequence of questions are generated by the Bayesian Adaptive Choice Experiment (BACE) or randomly (RAND), and when the coefficients are recovered using the Bayesian approach or using a maximum likelihood estimator (MLE).
The lighter color corresponds to higher value of true p, the parameter that corresponds to the probability of choosing randomly rather than choosing the choice with higher utility.
Rows are the four methods (see above).
Columns are the estimates after the number of questions asked.

Figure 11: Average mean squared error between true and estimated interaction coefficient when two amenities are presented

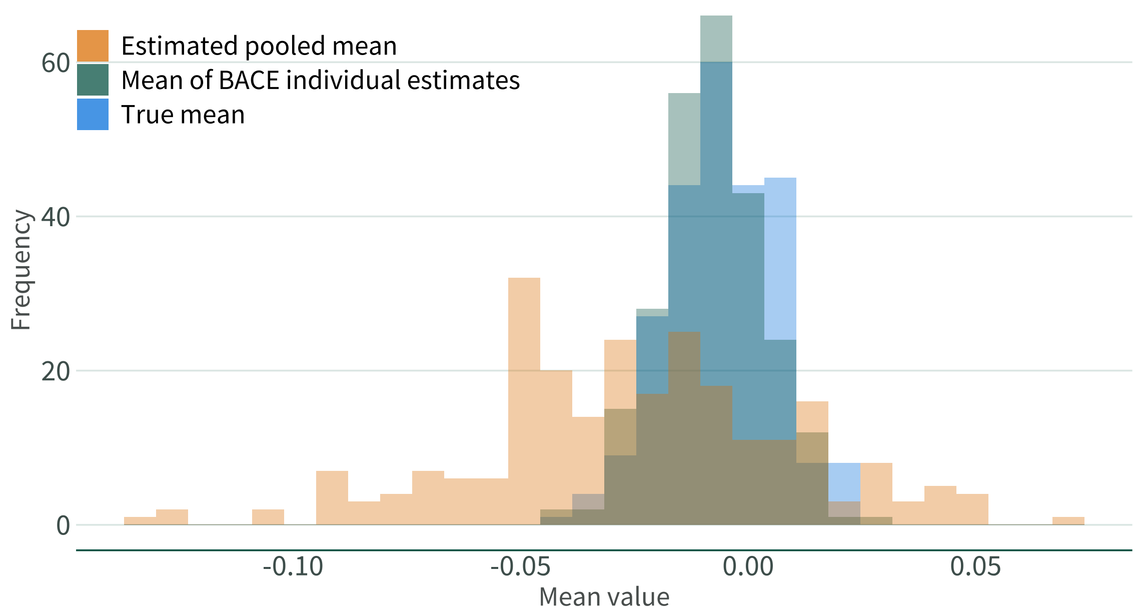


Note: The figure depicts the simulation results in the case when a binary choice is presented between two jobs which differ along three dimensions: earnings and the presence or absence of each of two amenities.
The x-axis is the number of questions used to obtain amenity coefficient estimates.
The y-axis is the average mean squared error between the estimates and the true values from the simulations.
The colors map to two methods: when the sequence of questions are generated by the Bayesian Adaptive Choice Experiment (BACE) or randomly (RAND).

Figure 12: Estimating population mean of γ from individual estimates vs. by pooling all answers



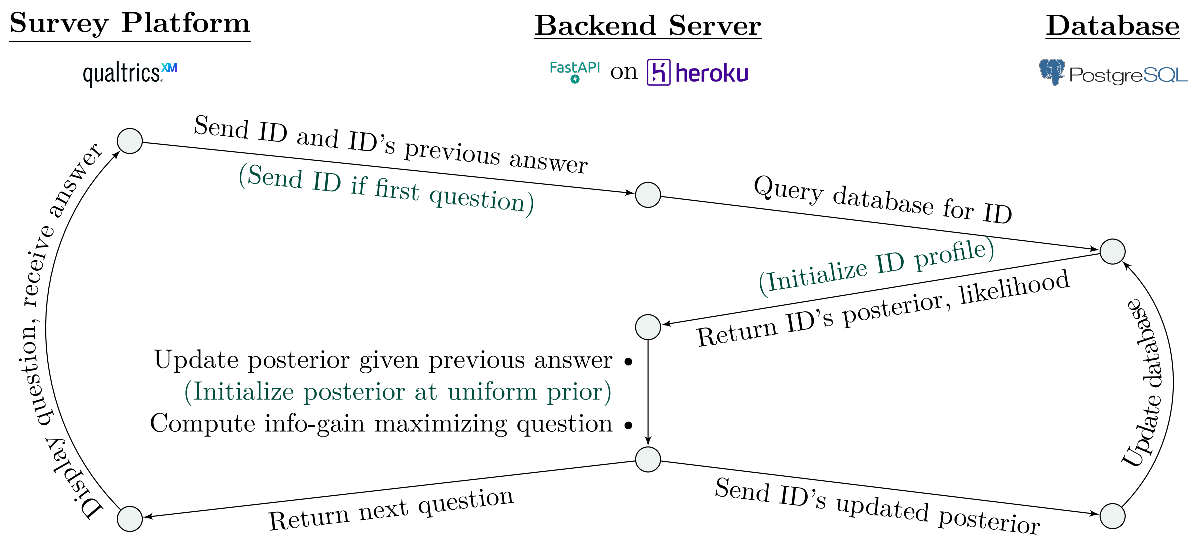
(a) Case 1



(b) Case 2

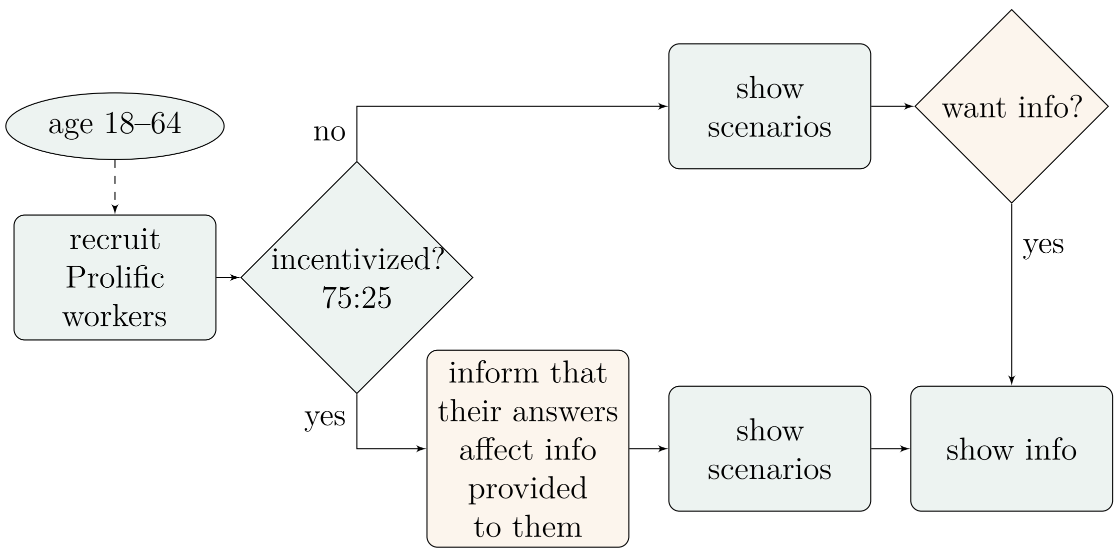
Note: Simulation result comparisons for estimating the mean γ in the generated data (blue) by averaging the BACE individual estimates (green) or by estimating the pooled data across all individual answers (orange). The number of scenarios per individual is held fixed at 20.

Figure 13: Implementation schematic



Note: A simplified schematic of the interactions between the survey platform and the backend computation and database servers.

Figure 14: Sample and experimental design

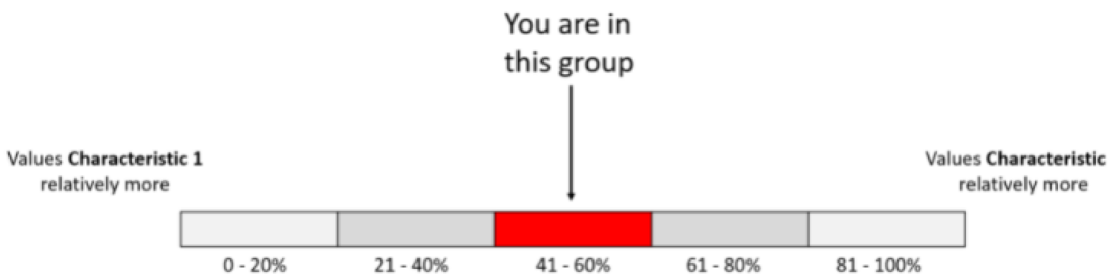


Note: This table summarizes the experimental design described in Section 3.1.

Figure 15: Incentive statement

Please answer all questions to the best of your ability. Your answers will be informative about how you value different job characteristics. At the end of the survey, we will share with you this information about yourself and about how your responses compare to others'.

An example of some information you can expect to see is in the below picture.



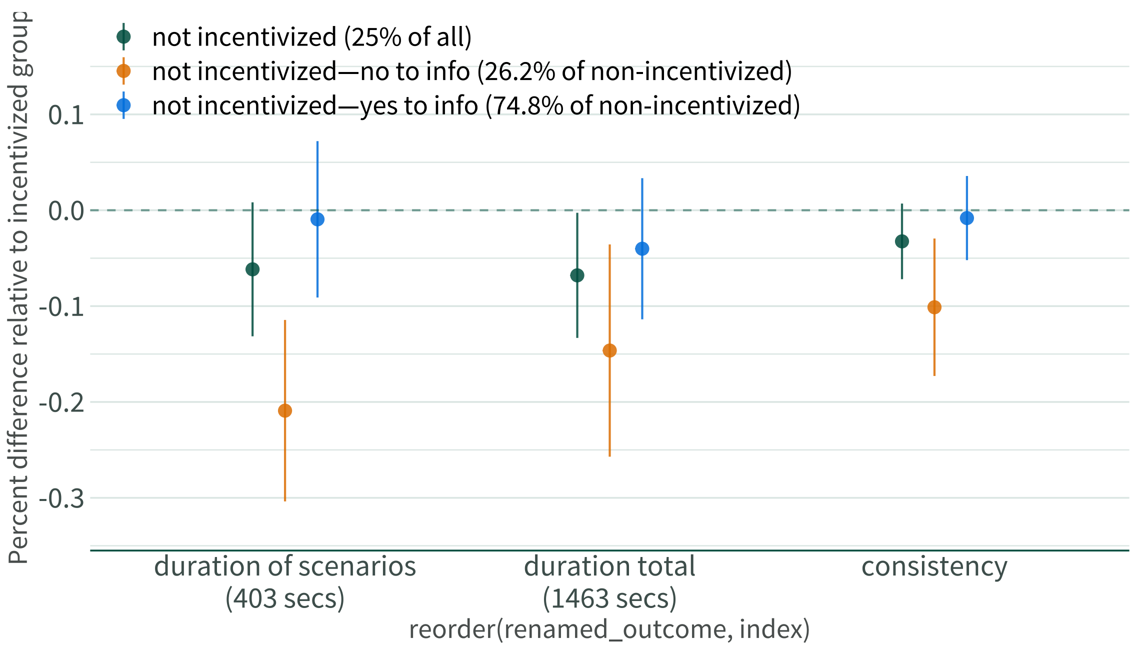
Based on the instructions, what will happen at the end of the survey?

- ○ I will be shown information about the jobs of people who value job characteristics similarly to me.
- ○ I will be shown information about jobs that are suitable for people like me.
- ○ I will be shown information about my valuations of job characteristics and how they compare to others'.

→

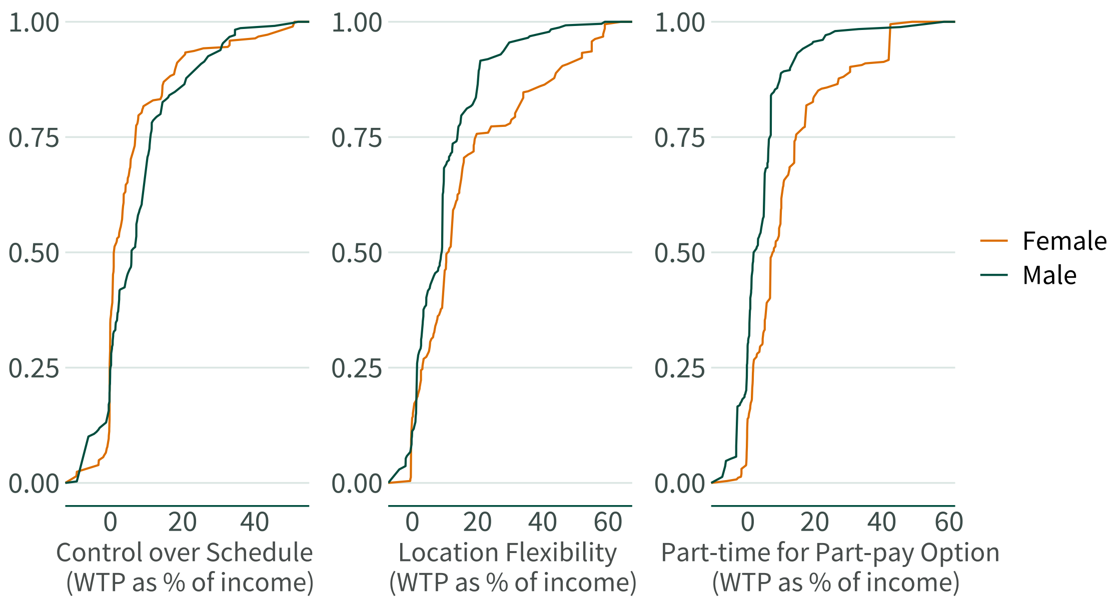
Note: See Section 3.1 for details on the incentive.

Figure 16: Effects relative to incentivized group



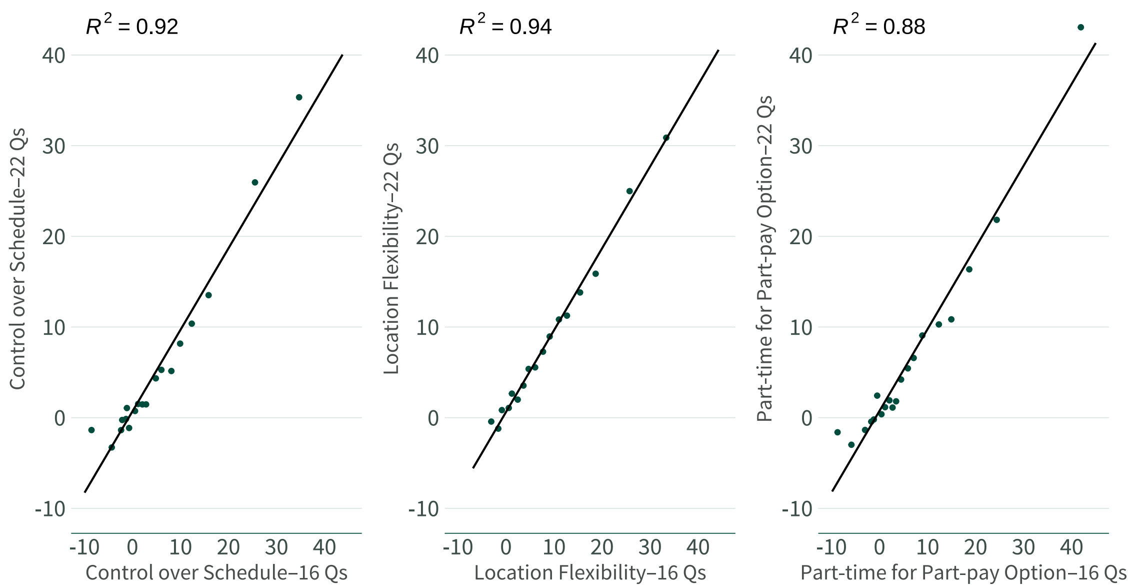
Note: See Section 3.1 for details on the incentive.

Figure 17: Individual WTP posterior estimates



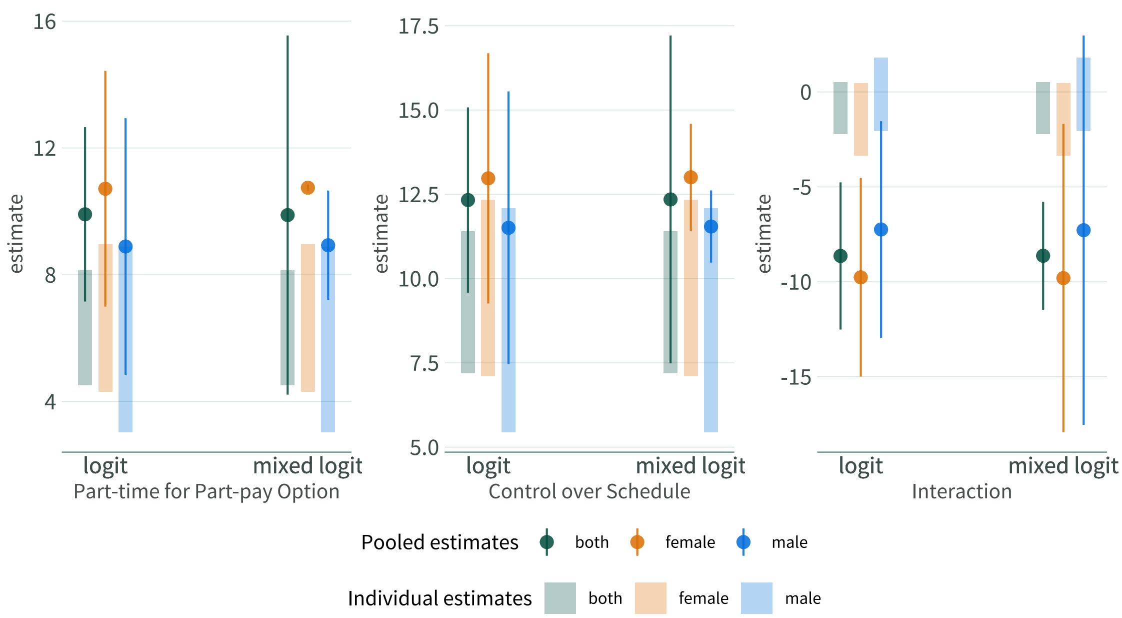
Note: This figure shows the empirical cumulative distribution of the individual WTP posterior estimates.

Figure 18: Estimate stability across questions



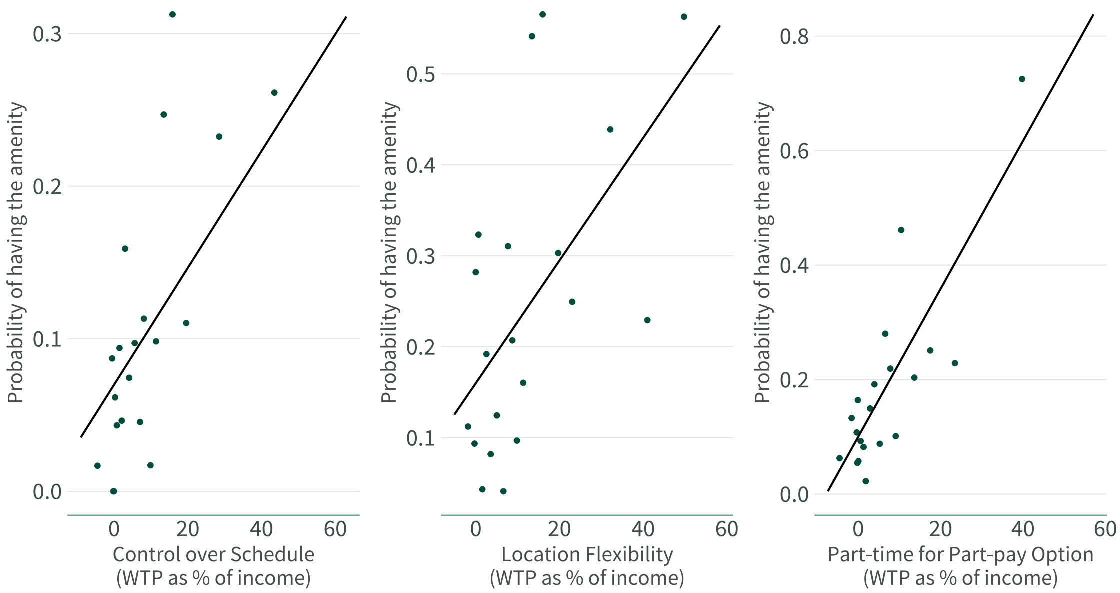
Note: This figure shows the empirical cumulative distribution of the individual WTP posterior estimates.

Figure 19: Mean parameter comparison to the standard pooling approach

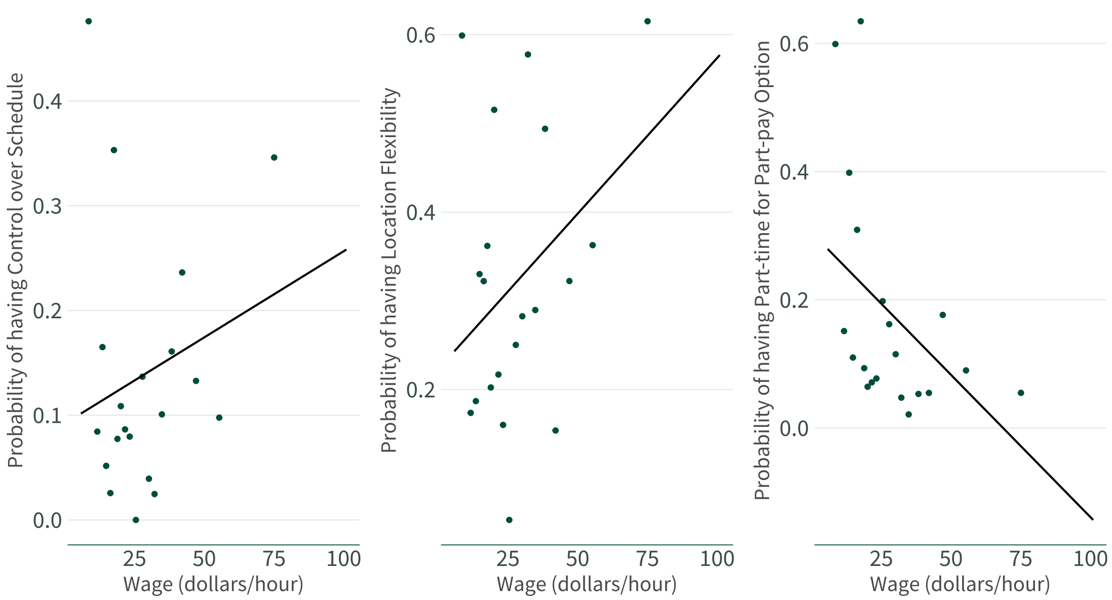


Note: This figure compares the mean of the individual-level WTP estimates to estimating the mean WTP when pooling together responses across all individuals.

Figure 20: Sorting by WTP and by wage



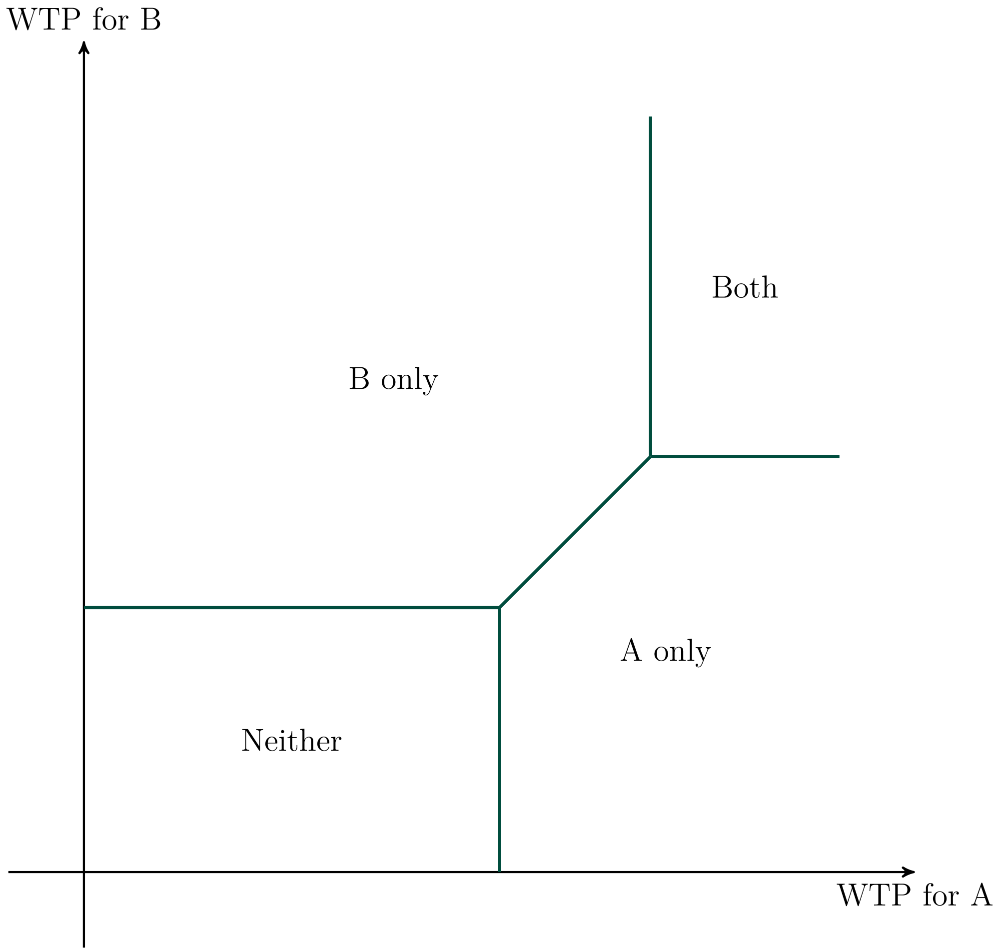
(a) Sorting by WTP



(b) Sorting by wage

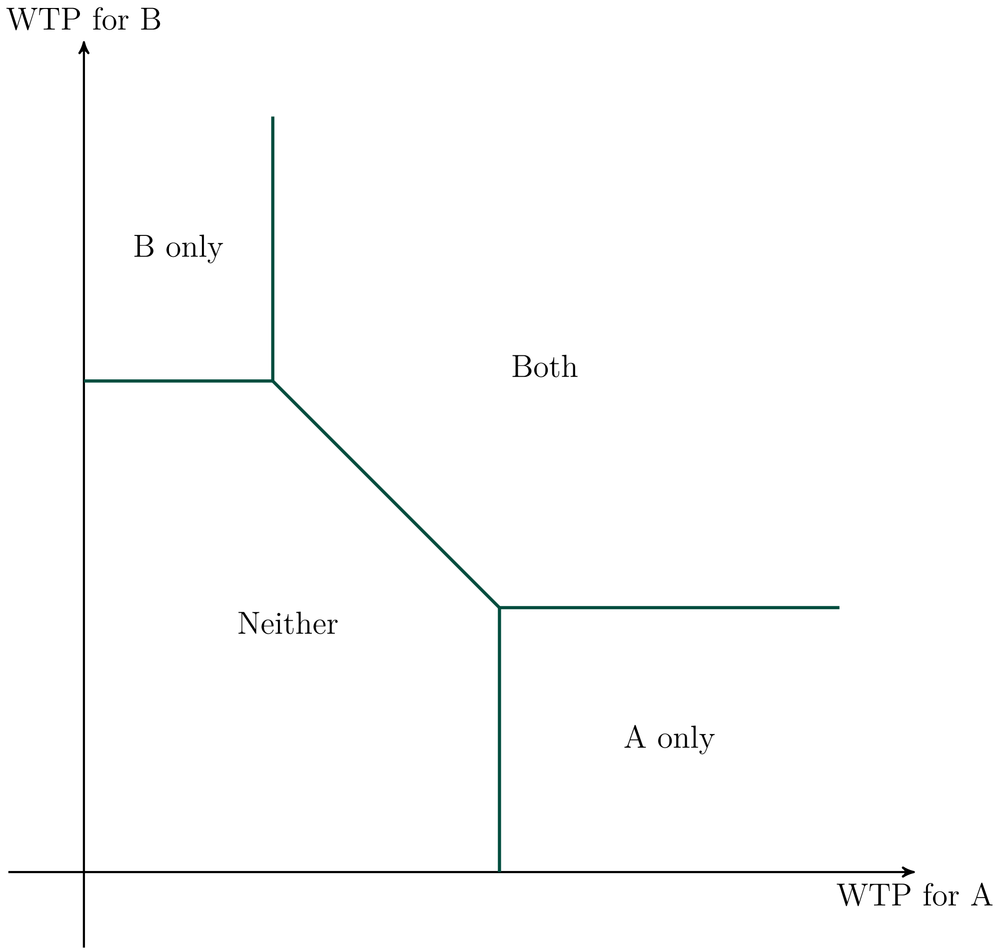
Note: The left panel shows the binscatter of WTPs and the probability of having the amenity. The left panel shows the binscatter of wages and the probability of having the amenity.

Figure 21: Sorting with two amenities: Positive price interaction



Note: This figure shows equilibrium demand for jobs with different amenity bundles in a case where the interaction between the amenity prices is positive.

Figure 22: Sorting with two amenities: Negative price interaction



Note: This figure shows equilibrium demand for jobs with different amenity bundles in a case where the interaction between the amenity prices is negative.

Table 1: Approaches to eliciting WTP with choice experiments

<table>
<tr><th colspan="2">Field, Hypothetical scenarios or Real choices</th><th>Hypothetical scenarios</th></tr>
<tr><td colspan="2">(+) Realistic sample currently facing job choices</td><td>(+) Flexible subpopulations</td></tr>
<tr><td>(+) Hypothetical: Flexible job options</td><td>(−) Real: Limited job options</td><td>(+) Flexible job options</td></tr>
<tr><td>(−) Hypothetical: Lack of incentive for effort</td><td>(+) Real: High-stakes incentives</td><td>(−) Lack of incentive for effort</td></tr>
<tr><td colspan="2">(−) If multiple options: Incentive (distortion) to appease potential employers
(−) If one random option: Cannot ask respondents to hold fixed expectations about non-displayed job aspects</td><td>(+) No incentive distortions and can ask respondents to hold fixed expectations about non-displayed job aspects</td></tr>
<tr><td colspan="2">Mitigation: If multiple options, language to balance between incentives (potentially affecting real outcomes) and distortion (no impact on employment chance)</td><td>Mitigation: Can add some incentives based on answers</td></tr>
</table>

Note: This table summarizes and comments on existing approaches to estimating WTP using discrete choice experiments.

Table 2: Amenities and Assigned Values

Job characteristic	**Base Value**	**Alternative Value**
Part-time for Part-pay Option	Have to work regular full-time (same total number of hours) each week	Have the option to work part-time, any number of hours up to regular full-time, prorated at the same wage rate
Control over Schedule	Has a fixed regular schedule that is a standard weekday morning-afternoon schedule	Can make up your own schedule to cover the full required hours each week
Location Flexibility	Have to work on-site, with no option to work remotely	Have the option of working remotely (e.g., from home) or working on-site

Note: List of job characteristics considered.
Willing-to-pay refers to the fraction of earnings one is willing to give up in order to have the Alternative Value instead of the Base Value.

Table 3: Reasons for not valuing flexibility

Control over Schedule	Location Flexibility	Flexible Hours
“I value the regular fixed schedule because it makes me follow a routine that i can get better and better at. *Making up my own schedule, while I CAN do that, makes me feel a little stressed.*”	“i value working on site *because total concentration is needed* in my job and i can’t afford to make any mistake that might cause the project to move in a slow pace, so working in a fixed environment is the best for me”	“Regular full time hours. *More money is the goal, so working less for less pay doesn’t make sense.* I have zero desire to work part time.”
“I have a personality that *if given my own path tend to slack and not meet goals*. I value strongly having a schedule set for me that I must stick too.”	“I have value working on-site because it enables me to concentrate more on my work. *Working at home come with a lots of distractions* from the kids.”	“I like the regular full-time hours. It *keeps me in a routine which is important to my well being*.”
“I like knowing what my schedule is going to be. Because I feel *more comfortable not having to make up my schedule*.”	“Work on site: It’s gives me *more time to work on my career*”	“The full time hours as it’ll *force me to keep up and keep learning and doing a good job*”

Note: Workers were asked if they value each amenity, why they do or do not. The table summarizes their given answers when they do not value each type of workplace flexibility.

Table 4: Model fit: Location flexibility

	Model	Data
Log wage	3.19 (0.04)	3.21
Std. log wage	0.53 (0.03)	0.54
Utility	3.34 (0.04)	3.27
Std. utility	0.58 (0.03)	0.56
Fraction with amenity	0.32 (0.03)	0.29
Frac. amenity | high wage	0.38 (0.04)	0.31
Frac. amenity | low wage	0.26 (0.04)	0.27
Amenity-WTP slope	0.94 (0.06)	0.81
Wage-WTP slope	-0.25 (0.12)	-0.22

Note: Standard errors are bootstrapped using 1,000 simulations.