Gig Rules: The Political Economy of Labor Market Regulations (Pre-analysis Plan An update on Appendix A2. Likely Driver Sample)

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Abstract

In response to the emergence of online platforms that match workers with specific tasks such as ride-sharing, coding, or handy work, lawmakers, regulators, and sometimes even voters created new rules to govern these novel forms of work. The regulations often seek to strike a balance between the benefits of gig work, primarily flexibility and autonomy, and the advantages of traditional forms of employment. In this paper, we study the welfare effects of a wide range of hypothetical job designs, using ride-sharing as our example. We ask three questions: First, if current and prospective drivers were to choose freely between different job designs, which features would be particularly attractive to them? Second, what are the design elements of jobs that find broad political appeal among voters? And third, what are the welfare consequences of imposing politically popular job designs on current and prospective drivers? To answer these questions, we use conjoint survey experiments to solicit preferences for job designs from both likely voters and prospective drivers. In our analysis, we first estimate voters' and drivers' preferences for each job attribute. Equipped with these estimates, we then predict the expected voter support for all possible job designs. Zooming in on designs that secure a majority of votes, we estimate drivers' decisions to drive as well as their well-being under these working conditions. Our project aims to expand the horizon on what ridesharing could look like and the welfare consequences of having voters and their representatives decide labor market regulations.

Keywords: gig work, labor regulation, voting behavior, job flexibility, conjoint survey experiment

JEL Codes: D72, J3, J8

1. INTRODUCTION

Faced with changes in technology and consumer demand, firms often update their work policies. While many of these changes are innocuous, some are hotly contested. A recent example are the working conditions of participants in the gig economy. Many online platforms provide workers with broad control over their schedules, but they classify the workers as independent contractors who forgo many of the benefits of formal employment. The resulting trade-off appears to be attractive to many. In the United States, nearly 10% of adults were engaged in gig work in a recent 12-month period, and a majority of them describe their pay and benefits as "fair" (Anderson et al., 2021).

Concerned about this rise in gig work, however, lawmakers who see the emerging work arrangements as hollowing out traditional employee protections stepped in. California's Assembly passed AB5, legislation that extended employee classification status to some gig workers (California, 2019). U.S. cities, including New York, Philadelphia and Seattle passed laws that secured better pay and protections (Cardin and Schild, 2021; Schifter, 2021). The European Union introduced rules that presume workers are employees

(Bourgery-Gonse, 2022). In response to these legislative efforts, some online platforms took the question of employee classification directly to the voters. Perhaps most famously, voters in California supported Proposition 22, a ballot initiative that allowed app-based companies to classify their workers as independent contractors (Luna, 2020.)1 Similarly, voters in Portland, Maine, rejected a referendum that would have classified gig drivers as employees. Voters in Washington rejected a law that required ride-sharing companies to provide workers' compensation insurance (Lima and Schaffer, 2022).

In this paper, we study the welfare consequences of having lawmakers and voters decide how to regulate gig work. We are specifically motivated by the binary narrative that ride-sharing companies push against potential regulations: Drivers can either enjoy the complete flexibility of driving "when, where, and as long as they want" or stick to a "rigid 9-to-5 schedule." This narrative motivated us to explore a wide range of possible job designs between these extremes. In particular, we conceptualize the ridesharing job as a bundle of attributes—e.g., wages, benefits, and specific work designs that influence flexibility and predictability—and each attribute may assume a range of values (e.g., the health benefit could be more or less generous, and a job could be more or less flexible).

Our data are generated by two sets of conjoint survey experiments, in which we ask voters to vote between a random hypothetical job versus the status quo and drivers about their willingness to drive personally for a random hypothetical job.

We plan to analyze these data in two steps. We first estimate voters' and drivers' preferences for each job attribute. Armed with these estimates, we can then predict the expected voter support for all possible job designs. Zooming in on designs that can expect to be supported by a majority of voters, we estimate drivers' decisions to drive as well as their well-being under these working conditions.

2. STUDY DESIGN

Our study consists of two surveys. The first solicits the preferences of likely voters. The second measures the preferences of three groups of gig-economy drivers: individuals who worked for companies like Uber or Lyft in the past; current drivers for these types of companies, and a third group, which we call likely drivers. The latter consists of people who might consider driving in the future, perhaps not under the current working conditions but under a broad range of possible ride-sharing job designs.

The broad structure of the two surveys is the same. (Appendix B presents the questions we ask.) Each survey includes a conjoint survey experiment that asks the respondents to evaluate a rich set of hypothetical working conditions. The surveys also include multi-choice questions that are designed to help us better understand the respondents' choices.

Below, we describe our samples, the conjoint survey experiments, and the motivations behind our non-conjoint survey questions.

2.1. Samples

We work with YouGov, a leading market research and polling company, to recruit participants and conduct our surveys. For the voting survey, we use a stratified sample that mimics the U.S. voting-age population. To identify the subset of likely voters in this sample, we ask respondents if they voted in past presidential,

[1] At the time of this writing, the fate of Proposition 22 is unknown after a judge invalidated the ballot initiative on constitutional grounds. The state's supreme court is expected to make the final decision (Hussain, 2022).

state-level and local elections. We also ask if they are likely to vote in the upcoming 2024 presidential election. Our goal is to collect about 3000 completed surveys.

While it is straightforward to select a sample of voting-age populations, identifying individuals who are likely to drive for companies like Uber and Lyft at some point in the future is more challenging. There is no ready information on what this subpopulation might look like, in particular for job designs that are not currently available in the market. We leverage our survey of likely voters to construct this sample. At the end of each conjoint experiment, we ask respondents how likely it is that they would consider driving for a ride-share company under the working conditions described in the experiment. We use these answers to identify demographic variables that predict a person's propensity to consider driving in the future. We then use these predictors to define the demographic strata of our likely driver sample. Our goal is to recruit 1000 participants who complete the likely-driver survey.

In addition to this sample of likely drivers, we also collect information from past and current drivers. We recruit these participants from YouGov, whose panel includes past and current drivers. Because the pool of driver-panelists is relatively small, we randomly select a sample of respondents, targeting 550 completed surveys. We may also recruit additional participants using other methods, for instance by working with influencers in the ridesharing industry and driver associations. We plan to combine the convenience samples of past and current drivers and weigh their responses based on the population characteristics of drivers published by Uber and Lyft.

Appendix A provides a detailed description of our sampling methods, and we discuss how our samples compare to population benchmarks.

2.2. The Conjoint Survey Experiments.

The design of our conjoint survey experiments is similar for both surveys. We ask each participant to complete eight tasks. In Task 1, the respondents evaluate a job profile that describes the working conditions that are typical of many of today's ride-sharing jobs. In Tasks 2-7, the participants compare two job profiles: Job A represents the status quo, the profile that the participants saw in their first task. Job B is a hypothetical, randomly populated job profile that differs from the status quo along multiple dimensions. To facilitate the comparison, we highlight in boldface the attributes of Job B that differ from Job A. The first seven tasks are identical across voter and driver surveys. The only difference is that we ask respondents to evaluate the job designs as voters ("would you vote for or against…") or drivers ("would you personally be willing to drive…"). The eighth task, which we describe in Section 3.2.3, differs across the two surveys.

In what follows, we describe the attributes that make up a job design and explain how the job profiles are randomized. Appendix B provides the questions and presents sample screenshots as respondents see them.

2.2.1. Job Attributes

We conceptualize jobs as bundles of attributes. A job design consists of ten attributes including compensation, work-related benefits (e.g., healthcare), and other elements such as work flexibility and the predictability of work schedules. We selected our attributes to reflect the most salient issues in the current debate over gig work. Table 1 presents the ten attributes, both their default and the alternative values.

<u>Compensation.</u>

Driver compensation varies along two dimensions.

1. *Mode of compensation*: How to measure work time is an important point of contention in current debates of ride-sharing.[2] Currently, drivers are paid based on "active time," which starts when the driver accepts a ride (and drives to pick up the passenger) and ends when the passenger is dropped off. "Wait time," the time between trips is not compensated. Reich (2020) estimates that wait time is about 35% of total work time, the sum of active time and wait time. In our survey, compensation for "active time" is the default. Alternative job designs compensate drivers for both active time and wait time.
2. *Hourly wage*: To determine the default hourly wage, we collect estimates of drivers' current compensation from proprietary data, industry reports and the literature. $18 per hour is our default because it is close to the average of our estimates.[3] We use $12, $15, $21, $24, $27, and $30 as alternative wage levels. The lowest level of compensation represents about a 33% reduction, and the highest level a 66% increase. We added a larger number of increases in compensation because many observers regard ride-sharing wages as low. It is useful to include wage reductions because these options help avoid dominated choices. For example, for jobs that maintain complete flexibility, a reduction in the hourly wage serves as a tradeoff when we increase job-related benefits such as health insurance.

   To make hourly compensation comparable across all job designs, we express compensation as dollars earned per hour on the job, including wait time. When drivers are paid based on active time, actual compensation can vary from hour to hour because wait times will vary. We tell respondents that "Drivers typically earn $X per hour on the job."[4] When drivers are paid for both active and wait times, we say "Drivers earn a fixed $X per hour on the job."

<u>Benefits.</u>

Our job designs include four types of benefits: health insurance, paid time off, workers' compensation, and unemployment insurance. We selected these benefits because they are often mandated in ride-sharing regulation (e.g., Prop 22 in California and HB 2076 in Washington), indicating their importance, and they are financially meaningful.[5] Worker's compensation is particularly relevant given the risks of driving.

3. *Healthcare*: Our default is the current situation; drivers are not covered by an employer-sponsored health plan. Alternative job designs provide two healthcare options. The less generous option conforms to federal law for employees: the company contributes financially to health insurance for

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[2] The eligibility of wait time is not only relevant for hourly wages but also for benefits such as healthcare. For example, Prop 22 stipulates that companies only contribute to healthcare if the active time accumulates to a certain threshold.

[3] Most of the existing estimates are based on California, Seattle, and New York City, which have relatively high wages, and not all estimates consider the wait time. Two exceptions are Hall and Krueger (2018), which include twenty markets, and Gridwise (2020) that covers 49 different cities. Specifically, Hall and Krueger (2018) use the drive survey data conducted by the Benenson Survey Group (BSG). The data show that in October 2015, the median hourly wage (considering wait time) is about $19 in all of the twenty markets covered by the survey. On the (relative) low end, it is about $15/hour in Chicago and $17/hour in DC. On the high end, it is $22.53 in SF and $23.13 in New York City. Gridwise is an app service for ridesharing drivers that automatically tracks mileage and earnings across multiple platforms. A 2020 report by Gridwise (Gridwise, 2020) summarizes the median earnings across 49 markets based on over 100,000 drivers. The median hourly wage ranges from $5.38 in El Paso (Texas) and $6.33 in Honolulu to $23.48 in NYC and $25.65 in Fresno CA. The median of the median earnings of the 49 markets is $16.46 per hour. We also have access to the detailed hour-level data of 301,147 drivers (and around 115.05 million hourly observations in total) in California from Lyft from February 1, 2019 to January 31, 2021. Our Lyft data show that the median hourly wage is about $16.65 per hour. The 25th and 75th percentiles are about $10.43 and $24.10 per hour. The mean is $18.50 per hour.

[4] Based on our conversations with the drivers, they also think about their compensation in terms of total time on the job, rather than only the active time. This is often called "app-on time" by the drivers.

[5] See https://www.bls.gov/news.release/ecec.t01.htm for a summary by the US Bureau of Labor Statistics on the costs of various employee benefits to employers.

drivers who work at least 30 hours per week.[6] The more generous option emulates the practice of employers such as Starbucks and contributes financially to health insurance for drivers who work at least 20 hours per week.

4. *Paid time off (PTO)*: Ride-share drivers currently do not have any PTO days. This is the default in our experiment. In a more generous job design, we offer respondents 18 PTO days that can be used at their discretion as vacation, sick days, and for personal reasons. 18 PTO days is the sum of vacation time and sick days that U.S. companies offer their employees on average. We focus on sick and vacation days because the law requires the full replacement of income for these absences from work.[7] Consistent with current practice, drivers are paid 100% of their average daily earnings during the previous quarter.
5. *Workers' compensation*: Our default is current practice in the ride-sharing industry, drivers are not covered by workers' compensation insurance. For job designs that offer this benefit, the employer-sponsored insurance will cover medical expenses and replace two thirds of driver income.[8][9] The fraction of replaced income varies from state to state, but two thirds is typical.
6. *Unemployment insurance*: Currently, drivers do not have unemployment insurance, which is our default. Alternatively, we let the company offer unemployment insurance. The U.S. average wage replacement rate was 0.450 in 2019.[10] Most states stipulate payment up to 26 weeks.[11] We use 50% for simplicity, which is the rate in Massachusetts.[12]

Work Design.

Academic research and industry surveys point to the drivers' ability to control their schedule and work for multiple ride-sharing companies as some of the most important benefits associated with ride-sharing (Chen et al., 2019, Benenson Strategy Group and GS Strategy Group, 2020). Full flexibility is the default in our survey. Alternative job designs limit flexibility in various ways. Specifically,

7. *Hours*: Currently, drivers freely choose how many hours they wish to work. Alternative job designs require drivers to work at least 10, 20 or 40 hours per week. A 10-hour requirement would constrain almost half of all current drivers.[13] Twenty- and 40-hour requirements map to a typical part-time and full-time job.
8. *Flexibility*: Today, ride-sharing companies do not impose shifts on their drivers. This is our default. In job designs with reduced flexibility, drivers provide their availability in 2-hour, 4-hour, or 8-hour blocks, and companies decide on the final schedules. This type of scheduling is common in

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[6] The Affordable Care Act (ACA) requires employers to provide health insurance for 95% of their full-time workers. Full-time is defined as working more than 30 hours per week. Source: https://www.cigna.com/employers/insights/informed-on-reform/employer-mandate.

[7] By contrast, family/medical leave (even in states that have such mandates) has a much lower wage replacement rate. On average, US private employers provide 7 days of sick leave and 11 days of vacation after 1 year of service. https://www.bls.gov/charts/employee-benefits/paid-leave-sick-vacation-days-by-service-requirement.htm

[8] Prop 22 in California, which is supported by ride-sharing companies, stipulates the following benefits related to worker injuries: Company-provided occupational accident insurance for at least $1 million in medical expenses and lost income resulting from injuries suffered while the driver is online and available to receive service requests; Disability payments equal to 66% of a driver's average weekly earnings during the previous four weeks before covered injuries, for up to 104 weeks; Company-provided accidental death insurance for the benefit of driver's spouse, children, or other dependents when driver dies while using the app. Our proposed worker's compensation insurance is more generous than Prop 22 in that it does not have a cap on the total medical expenses and lost wages.

[9] https://www.findlaw.com/injury/workers-compensation/workers-compensation-laws-by-state.html

[10] https://oui.doleta.gov/unemploy/repl_ratio/repl_ratio_rpt.asp

[11] https://oui.doleta.gov/unemploy/content/sigpros/2010-2019/January2019.pdf. https://www.cbpp.org/research/economy/how-many-weeks-of-unemployment-compensation-are-available

[12] https://www.mass.gov/info-details/how-your-unemployment-benefits-are-determined#:~:text=If%20you%20are%20eligible%20to,amount%20is%20%20%241015%20per%20week.

[13] According to our Lyft data, 52.87% of drivers work more than 10 hours per week, 21.99% of drivers work more than 20 hours per week, and 3.32% percent of drivers work more than 40 hours per week.

retail, for instance. Two-hour blocks correspond to the modal work time of current drivers.[14] 8-hour blocks are typical taxi shifts.[15]

9. *Predictability*: For individuals who work in company-set shifts, the predictability of their assignments is a major concern (Goldin, 2020).[16] In job designs with shifts, we place three levels of restrictions on companies. Once assigned, they cannot cancel or change shifts at all, or they have to give at least 1 day's or 7 days' notice.[17]
10. *Drive for other platforms*: Currently, drivers can drive for multiple ride-sharing companies.[18] In a more restrictive job design, we do not allow drivers to multi-home.

2.2.2. Randomization and Restrictions

All respondents first evaluate our default job design. Next, they compare the default design with randomly chosen designs, which we refer to as Job B. For any Job B, the value of each attribute is randomly assigned with equal probability from all possible values. The choice of a value for each attribute is independent across attributes, with the exception of two restrictions.

First, flexibility and predictability are linked. When drivers control their own schedules, these schedules are naturally predictable. Thus,

<u>Restriction 1:</u>

- If the flexibility attribute takes the default value of "drivers can freely choose when they work," the predictability attribute also takes the default value: "Drivers know in advance when they will work because they control their schedules." We choose the default value of flexibility with a probability of 25%.
- Conversely, when drivers work in company-assigned shifts, predictability takes on one of the three alternative values with equal probability.

We also impose a second restriction to rule out job profiles that we expect to dominate or be dominated by the status quo. We eliminate these designs because they do not present any tradeoffs. Specifically, we expect that for any of the four benefit attributes, the respondents would prefer the alternative values to the default. By contrast, because all of the work design attributes limit job flexibility in some fashion, we expect the respondents to prefer the default value to the alternative. Based on these expectations, we impose the following restrictions:

<u>Restriction 2:</u>

We eliminate a potential Job B from our set of job designs if it does not satisfy any of the following three criteria:

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[14] If so scheduled, drivers can work for several consecutive two-hour blocks if they choose to.
[15] About 25% of driving segments are four hours or longer.
[16] "During those periods in their life cycle, some prefer to work specific hours, including students who cannot work during class and parents who must be home to care for children, even if they work regular or long hours." "Furthermore, many prefer to work predictable hours rather than being on call or working at the whim of an employer even if they work 40 hours or more per week."
[17] Some cities (notably San Francisco and Seattle) require employers to give more advance notice of schedule changes or pay extra to employees. In Seattle, for example, employers need to pay modest "predictability pay" if they require a worker to come in for a shift with less than two weeks' notice to account for the impact on workers. Source: https://hrdailyadvisor.blr.com/2017/01/24/what-is-predictable-scheduling/.
[18] According to a Lyft report, 67% of Lyft drivers work on other app-based platforms. https://drive.google.com/file/d/1f65ajzda0pp5csSHGYet2uaMr2Kfm3E9/view

- If the hourly wage of Job B is higher than that of Job A, at least one of the four work design attributes needs to take on an alternative value.
- If the hourly wage of Job B is lower than that of Job A, at least one of the four benefit attributes needs to take on an alternative value.
- If the hourly wage of Job B is the same as Job A, at least one of the benefit attributes, as well as at least one of the work design attributes, need to take on alternative value.

2.2.3. Evaluation of the Job Designs

As discussed earlier, our goal is to have individuals evaluate the different job designs in their role as voters who help set regulations for gig work or their role as (likely) drivers who consider working at companies such as Uber and Lyft. We begin by discussing the evaluation questions for voters.

Likely Voter Survey

Following the presentation of the current working conditions (Task 1) and a pair of job profiles (Tasks 2-7), we ask "In some states, citizens are asked to vote on laws that describe permissible working conditions. If you face this question, would you vote for or against this work arrangement?" The respondent can "vote for" or "vote against." In a follow-on question (Tasks 2-7), we ask: "If you had to choose between Job B and Job A, which one would you vote for?"

Data generated by both questions can be used to identify the participants' preferences for specific job attributes. The first question evaluates job designs on an absolute scale. It might well be that some respondents reject most of our designs as unacceptable. The forced-choice question provides a relative valuation of the paired designs.

Before collecting demographic data from the likely voters, we present an eighth task that we can use to draw a sample of likely drivers. We present the same pair of jobs (as in Task 7) and ask: "If you considered working for a ride-sharing company at some point in your career, would you personally be willing to drive under each of the following working conditions?" The respondent answers using a seven-point scale that ranges from "Definitely Not" to "Definitively Yes."

Driver Surveys

We use three versions of our driver survey (for past, current and future drivers) to measure the appeal of our job designs. The substance of the three surveys remains the same but the wording reflects the respondent's status.

We first present drivers the default job design (Task 1) and ask, "How attractive do you find these working conditions?" In Tasks 2-7, we ask, "How attractive do you find Job B?". The respondents rate the attractiveness of the designs on a 7-point scale that ranges from "very unattractive" to "very attractive." Following Tasks 2-7, we also ask a forced-choice question: "Which working conditions do you find more attractive, Job A or Job B?" In a third question, we ask about the participant's willingness to drive personally if offered the default job or any of the alternative designs: "If you considered working for a ride-sharing company at some point in your career, would you personally be willing to drive under these working conditions?" The respondents can answer yes or no.

The answers to the above questions show whether a participant would be willing to become a driver under our conditions. For a separate project of ours that will use the survey data, we are also interested in how many hours a respondent would drive given a particular design. To collect this information, we randomly select one of the seven jobs (i.e., Job A and six Job Bs) a respondent has seen previously after Task 7. If the respondent had accepted this job, we ask: (1) “How many hours do you think you would drive on a typical day?” and (2) “In a typical week, how many days do you think you would drive for the company?” Respondents who had rejected their randomly chosen design earlier in the survey would not see this eighth task.

In follow-up questions to Task 8, we also ask whether the participants expect to drive about the same number of hours every week or not; and if the hours are likely to be different, what might be the reason. These questions allow us to get a sense of how the participants value flexibility and predictability. We can cross-validate these answers with the estimated preferences from the conjoint experiment.

2.3. Demographic Questions

The YouGov panel provides regularly updated demographic information such as age, education, employment, family income, and political engagement.

In the voter survey, we supplement the YouGov panel with questions that are designed to capture the degree to which voters can relate to ride-sharing drivers. For example, we ask if they had ever worked in the gig economy, how often they use the services of companies such as Uber and Lyft, and how familiar they are with drivers’ working conditions. A second set of questions concerns the degree of flexibility and predictability of the respondents’ own jobs. The idea is that the participant’s own experience with workplace flexibility might color their view of our job designs.

We add two types of questions to the driver survey. We ask current and past drivers about their actual driving hours. (We already know how long they would drive under one of our hypothetical designs if they had accepted the job.) The answers might allow us to see how responsive work hours are to changes in job design. We also want to know more about why the respondents value some attributes as particularly important. For instance, we ask if the respondents already have health insurance from a source other than gig work.

3. DATA

The Online Appendix provides a full description of our sample. Specifically, we provide:

- a table that compares our samples to benchmark populations.
    - For the voting survey sample, we will compare the demographics of our sample to the U.S. adult population as described in the 2019 American Community Survey
    - For the driver samples, we will compare their demographics to the sample characteristics of Uber and Lyft drivers.
- a table that documents attrition as well as comparisons of the demographics of respondents who do and do not complete the survey.

4. EMPIRICAL METHODS (AND PRE-ANALYSIS PLAN)

Our analysis consists of two parts. First, we estimate the marginal value of each job attribute, separately for likely voters, likely drivers, as well as current and past drivers. We group current and past drivers because of the relatively small sample sizes. The resulting estimates help us understand how our respondents trade off various job attributes. We can also see if the tradeoffs vary across voters and drivers. Second, we use the estimates to conduct counterfactual analyses. Specifically, we are interested in predicting driver participation rates and wellbeing for regulatory regimes that are likely to win the majority support of the voters.

4.1. Marginal Value of Individual Job Attributes

Respondents' ratings ("how attractive…) and forced-choice answers ("which do you find more attractive") both allow us to estimate the marginal value of individual job attributes. Our focus will be on models for voters that are based on the forced-choice questions and models for drivers that draw on our ratings question. Our choice reflects real-world circumstances: Voters are typically asked to vote for or against a policy proposal relative to the status quo, the default job in our case. However, when choosing a job, it is natural to compare a specific job option to outside employment options; it would be odd to force someone to make a choice between two, possibly inferior, job opportunities.

We illustrate our empirical model using the forced choice data from the voting survey. Because Job A stays the same throughout the six comparison tasks, the respondent compares a changing alternative to the same constant utility. Thus, the data-generating process is the same as the canonical discrete-choice model, in which the decision-maker chooses between an option and an outside option that is normalized to zero. Because each respondent is asked to compare six job pairs, we have N*6 observations, where N is the number of respondents in the voter survey. For simplicity, we estimate a linear probability model:

$$\begin{aligned} \mathrm{V_{ij}} = {} & \beta_0 + \beta_1 \mathrm{Mode_j} + \beta_2 \mathrm{Wage_j} + \beta_3 \mathrm{HI30_j} + \beta_4 \mathrm{HI20_j} + \beta_5 \mathrm{PTO_j} + \beta_6 \mathrm{WC_j} + \beta_7 \mathrm{UI_j} + \beta_8 \mathrm{Shift_j} \\ & + \beta_9 \mathrm{Shift_j^{4h}} + \beta_{10} \mathrm{Shift_j^{8h}} + \beta_{11} \mathrm{Shift_j^{7d}} + \beta_{12} \mathrm{Shift_j^{1d}} + \beta_{13} \mathrm{10h\ min_j} + \beta_{14} \mathrm{20h\ min_j} \\ & + \beta_{15} \mathrm{40h\ min_j} + \beta_{16} \mathrm{Exclusivity_j} + \omega_j + \beta_X X_j + \epsilon_{ij}, \end{aligned}$$

where $\mathrm{V_{ij}} = 1$ if respondent *i* votes for Job B in comparison task *j*, and $\mathrm{V_{ij}} = 0$ if she votes for Job A. The right-hand side variables are the job attributes of Job B. $\mathrm{Mode_j}$ indicates how the driver is paid, the default being active hours. $\mathrm{Wage_j}$ is a linear measure of the wage variable; $\mathrm{HI30_j}$ and $\mathrm{HI20_j}$ are dummies indicating whether the compensation includes health care for drivers working more than 30 or 20 hours; $\mathrm{PTO_j}$, $\mathrm{WC_j}$, and $\mathrm{UI_j}$ are dummy variables indicating whether the compensation includes paid time off, workers' compensation, or unemployment insurance.

Shift_j is a dummy indicating that drivers work in company-set shifts rather than controlling their own schedules. The coefficient, β_8, captures the difference in utility between the least restrictive shift schedule (i.e., 2-hour shifts that cannot be canceled or changed) and the baseline case in which the drivers control their schedules. If drivers value flexibility, β_8 will be negative. Shift_j^{4h} and Shift_j^{8h} indicate 4-hour and 8-hour shifts, and Shift_j^{7d} and Shift_j^{1d} indicate that the company can cancel or change shifts with 7-days' or 1-days' notice. The coefficients of these four variables are incremental additions to β_8. They reflect increasingly restrictive or less predictable schedules. The next four variables capture the remaining restrictions on flexibility. Three dummies, $\mathrm{10h\ min_j}$, $\mathrm{20h\ min_j}$, and $\mathrm{40h\ min_j}$ indicate minimum 10-hour, 20-hour, and 40-hour worktime requirements. $\mathrm{Exclusivity_j}$ indicates that the driver cannot drive for other platforms.

Finally, ω_j are dummies for the number of tasks that the respondent completed. We use it to control for any sequence effects. X_j are demographic characteristics provided by YouGov and our survey. We also run specifications that include respondent fixed effects α_i that account for different average ratings across respondents. We present results for both unweighted as well as weighted regressions.

Note that all non-wage coefficients, when divided by the coefficient of Wage_j, represent dollar values of the job attributes. For example, having health insurance that provides coverage for drivers who work more than 30 hours is equivalent to improving hourly wage by $\frac{\beta_3}{\beta_2}$.

The regressions using independent ratings data are analogous to the model above. In these models, the dependent variable is whether the voter votes for or against a given job profile. Because each voter rates seven unique job profiles, this regression uses N*7 observations. Conceptually, ratings and forced-choice data should generate similar estimates of all of the coefficients except for the constant. The constant is different because the respondents face different outside options; it is Job A when using forced-choice data, and it is the respondent's lowest-standard of permissible working conditions when using independent ratings data.

4.1.1. Comparison across Survey Samples

One aim of the paper is to identify the changes in driver welfare if we delegate rulemaking to voters. To begin, we investigate whether voters and drivers differ in their preferences. Econometrically, we can identify such differences by pooling our samples and implementing two-way interactions (e.g., $\text{HI30}_\text{j} \times \text{driver}$). If the differences are significant, we plan to explore the possible sources of these differences: Do they primarily come from the demographic differences between the voter and the driver populations? Or does the respondent's identity—driver vs. voter, drive any differences?

4.2. Expected Voter Support of Hypothetical Job Designs and Their Impact on the Ridesharing Labor Market

In this section, we first use the voting survey data to calculate the predicted share of "yes" votes for all our job designs relative to Job A. Because the voting survey sample reflects the general adult population, we plan to adjust our predictions by a respondent's likelihood of voting. Several questions in our survey—whether they have voted in past presidential and local elections and how likely they are to vote in the upcoming 2024 presidential election will help us identify likely voters. Another possibility is to weigh all of our observations by the predicted likelihood of voting, as in Rentsch et. al (2019).

In a similar exercise, we can predict the labor participation rate of drivers for each of our job profiles.

We can then produce a scatterplot of these two predictions, the x-axis being the predicted share of "yes" votes associated with a given job design and the y-axis the predicted labor participation rate of the same design. This scatterplot is interesting as it answers two important questions. (1) How closely correlated are voter and driver rankings of job designs? And (2), what job designs that are supported by a majority of voters will yield the highest labor participation rates?

Because we can express the monetary value of individual job attributes as certain equivalent changes in the hourly wage, we can add up all these marginal values and arrive at a dollar value of the attractiveness of a job that features specific attributes. These assessments will be at the unit of hourly wage; for example, relative to the status quo, the welfare improvement (or reduction) of a hypothetical job X is equivalent to raising (or decreasing) the hourly wage by \$X. With these numbers, together with reasonable assumptions of the number of hours one may drive if accepting a job, we will be able to provide an assessment of welfare changes when we change to a regulatory environment that would sustain different working conditions for ride-sharing workers.

We can also use these estimates to predict the political support, labor participation rate, and the hours driven under specific policy proposals such as California's Prop 22 and AB5, as well as the current regulations in NYC and Washington State.

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TABLES AND FIGURES

Table 1: Job Attributes and Values

Dimension		**Values**
Mode of compensation	Default	Drivers are not paid for the wait time between rides.
	Alternative	Drivers are paid for every hour on the job, including the wait time.
Compensation	Default	Drivers typically earn $18 per hour on the job.
	Alternative	[If default mode of compensation] Drivers typically earn $12 [$15, $21, $24, $27, $30] per hour on the job. [If alternative mode of compensation] Drivers earn a fixed $12 [$15, $18, $21, $24, $27, $30] per hour on the job.
Health insurance	Default	None
	Alternative	The company contributes financially to health insurance for drivers who work at least 20 [or 30] hours per week.
Paid time off	Default	None
	Alternative	The company provides 18 days of Paid Time Off (PTO) for sickness, vacation, and personal days. Each day off, drivers earn their average daily compensation during the previous quarter.
Worker's compensation	Default	None
	Alternative	Company provides workers' compensation. Workers' compensation covers the cost of work-related injuries. When drivers cannot work at all, they earn 66% of their average daily compensation during the previous quarter.
Unemployment insurance	Default	None
	Alternative	Company provides unemployment insurance. Drivers earn 50% of their average daily compensation during the previous quarter for up to 26 weeks when they are unemployed.
Hours	Default	Drivers can freely choose how many hours they work each week.
	Alternative	Drivers are required to work at least 10 [or 20, 40] hours per week.
Flexibility	Default	Drivers can freely choose when they work.
	Alternative	Drivers provide their availability in 2- [or 4-, 8-] hour blocks. The company decides on their final schedules.
Predictability	Default	Drivers know in advance when they will work because they control their schedules.
	Alternative	[Alternative 1] The company cannot change or cancel scheduled shifts. [Alternative 2] The company can change or cancel scheduled shifts, giving at least 1 day's notice.] [Alternative 3] The company can change or cancel scheduled shifts, giving at least 7 days' notice.]
Drive for other platforms	Default	Drivers can drive for multiple ride-sharing companies.
	Alternative	Drivers are not allowed to drive for other ride-sharing companies.

Appendix A. Sampling Methods

A1. Voting Survey Sample

YouGov uses a sample matching methodology to select representative samples from non-randomly selected pools of respondents. YouGov's sampling frame is based on the 2019 American Community Survey (ACS) public use microdata file. To achieve political balancing, YouGov also includes additional voting behavior variables in its models, using data from the 2020 Current Population Survey (CPS) Voting and Registration supplements and the 2020 National Election Pool (NEP) exit poll. Typical general (adult) population target samples are selected using proportionate stratified sampling, whereby strata are defined by age*race*gender*educ, region, 2020 presidential vote, and home ownership (a proxy for socio-economic status).

Having defined the target sample, YouGov uses a two-stage process to select a matched sample from its panel:

Stage 1: Survey fielding. The company uses a proprietary method known as "turbosampling" to randomly invite and assign opt-in panel members to surveys based on demographic and scheduling needs of each survey. Specifically, every 30 minutes, YouGov's survey system evaluates the sample needs of all surveys it conducts in the field, selects a random sample from the whole panel, and invites the members of that random sample who are currently eligible for a survey (based on a match between their profiled demographics and each survey's demographic targets). When a panelist responds to a YouGov invitation, the system selects the survey where that panelist is most needed and sends them there. Thus, respondents to any given survey are randomly sampled indirectly, based on the aggregated sample needs of many surveys. Turbosampling adjusts dynamically to assign respondents based on current demographic needs of each survey. As fielding progresses, cells fill up, and only respondents of a certain type are still accepted into the survey.

Stage 2: Survey post-processing. YouGov collects excess responses during the fielding stage and uses proximity matching to find a final matched case from its panel participants for each observation in the target sample.[19] Proximity matching allows more granular matching on the joint distribution of variables. Variables used for proximity matching of general population samples typically include gender, age, race and education.

The matched cases are then weighted to the sampling frame using propensity scores and post-stratification. While the sample still requires weighting, weights are more efficient thanks to the previous two stages of matching. With propensity score matching, the matched cases and the frame are combined, and logistic regression is used to estimate the probability that a case comes from the frame or the matched sample. Each case receives a weight equal to the estimated probability that it comes from the frame divided by the estimated probability that it comes from the matched sample. Cases with a low probability of being from the matched sample are underrepresented relative to their share of the population and receive large weights, and vice versa. The propensity score function includes a variety of demographics, including age, gender, race, education, and region. Post-stratification weighting is used as the last step to force the final distribution

[19] According to YouGov, for each variable used for matching, a distance function, d(x,y) is defined to capture how "close" the values x and y are on a particular attribute. The overall distance between a member of the target sample and a member of the panel is a weighted sum of the individual distance functions on each attribute. The weights can be adjusted for each study based upon which variables are thought to be important for that study, though, for the most part, the matching procedure seems insensitive to small adjustments of the weights. A large weight, on the other hand, forces the algorithm toward an exact match on that dimension.

to be a certain percent, including the desired vote choice distribution and the four-way distribution of gender, age, race and education.

A2. Likely Driver Sample

We use stratified sampling to draw a sample of likely drivers from YouGov's panel. Our target population consists of people who consider driving under some of the job designs in our conjoint experiments. To identify this population, we start with a representative sample of people who can drive and present them with two randomly chosen job profiles. For each of these, we ask whether they would consider driving under these circumstances. Our target population are respondents who say yes.

More specifically, we take the following four steps to create our sample of likely drivers:

Step 1: Leverage our voting survey to solicit respondent's willingness to drive.

Properly weighted, our survey of voters provides a representative sample of the general adult population that is old enough to drive. We solicit their willingness to drive given specific job designs at the end of the conjoint experiment. After the respondents vote on their 7th pair of job designs, they see the same pair on a new screen, and we ask, "If you considered working for a ride-sharing company at some point in your career, would you personally be willing to drive under each of these working conditions?" The respondents provide their answers on a 7-scale that ranges from "1 - definitely not" to "7 - definitely yes" for both jobs. We can then relate this willingness to drive to the respondents' demographics.

Step 2: Identify the stratifying variables

To create a sample of likely drivers that resembles the broad majority of gig drivers, we exclude respondents who are older than 70 (about 15% of the voting survey sample), those with a family income in the highest two categories of the YouGov income scale (i.e., incomes greater than $350k and corresponding to 1.33% of the voting survey sample), and respondents who prefer not to disclose their income because we want to be able to control for family income in subsequent analyses (9.10%). Collectively, imposing these criteria excludes 23.3% of the voting survey sample.[20]

For the remaining respondents, we conduct a series of analyses to identify the demographic variables that are most predictive of the respondents' willingness to drive (WTD). We define WTD using the 7-scale answer in our survey and create two dummy variables: YesDrive is the more stringent—it indicates WTD >= 6 ("very likely yes")—and YesDrive2 is a broader cut, indicating WTD >= 5 ("likely yes"). We run linear probability and logit models using the two indicators as our dependent variables, and OLS and quantile regressions (80th and 90th percentile) with WTD as the dependent variable.[21] All regressions include the job characteristics, which are important determinants of a respondent's willingness to drive. These regression results are available upon request.

[20] Minor adjustments of these criteria (e.g., changing the age threshold to 65 or the income threshold to $250k) do not result in meaningful changes to how we stratify our sample.

[21] Before running the regressions, we lightly pre-process some variables that include many categories to avoid small bins. We group the values based primarily on the raw data averages of the outcome variable. We also consider the proximity in the meaning of these categories; for example, people with part-time and temporary jobs are grouped together, in contrast to people with full-time jobs and those who are retired.

Across all our specifications, we find that the predictive power of our models is quite poor. Typical values of R-sq are around 0.07. Root-mean-square deviations (RMSE), the average difference between the predicted values and the actual values, are about 0.40, a large deviation.[22]

Multiple factors help explain the limited explanatory power of our models. First, driving is a general-purpose skill with broad appeal in the population. Unlike other forms of gig work that tend to attract people with moderate levels of education and income (Katz and Krueger, 2019), we find that race, gender, income, and education are not significant predictors of our respondents' WTD. As a practical matter, we are limited in our exploration of variables that might proxy for heterogeneity because our models can only include variables that match the questions which appear in the standard YouGov panel. We can also run regressions with fixed effects because respondents indicate their WTD for two different job designs. But even in these regressions, R-sq remains modest (the overall R-sq is about 0.04), suggesting the decision to drive is mostly influenced by unobserved variance across tasks.

While the explanatory power of our models is limited, we can identify five predictors of WTD that are consistently statistically significant and economically sizable: *the importance of religion, interest in politics, age, having children under 18, and employment status*. Some of these results are more intuitive than others. Note, however, that we are not interested in a causal interpretation of these associations; we include them in our analysis solely for their predictive power.

We assess the relative importance of the five demographic variables in OLS and linear probability models, by calculating the reduction in R-sq when a variable is removed from the full regression, and by implementing random forest and decision tree models that provide metrics on how important a variable explains the data. Across the models, we find that four variables—the importance of religion, interest in politics, age, and having children under 18—are consistently ranked high in terms of their predictive power. By contrast, employment status has a more marginal influence in some of our specifications. As we explain in the next section, we end up using all five variables as the stratifying variables.

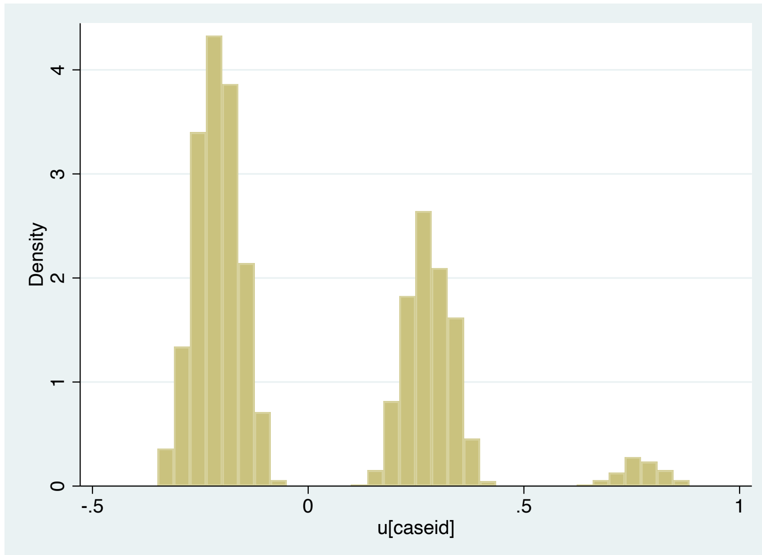
Step 3: Define the strata.

We use the results from a decision tree model— specifically, a Chi-square automatic interaction detection model commonly used in segmentation studies (Kass, 1980; Biggs, de Ville and Suen (1991)—as the basis for stratification. Decision tree models optimally merge the levels of splitting variables—for instance, the importance of religion is measured on a scale from 1-4 in our data, and the algorithm merges the four levels into two—and they search for combinations of the merged splitting variables that have the greatest predictive power. These combinations correspond to the strata in our study. Because there is a single tree, we can clearly see how the variables are split and how the subjects are grouped into different clusters.

In our application, WTD is influenced both by demographics and by the design of the jobs that the respondents evaluate. We cannot include the latter information in the decision tree model itself because the job design variables are not available in the standard YouGov panel. To address this issue, we use the respondents' average WTD as the dependent variable in the decision tree model. Specifically, we estimate a linear probability model with YesDrive as our dependent variable and include the job attributes and individual fixed effects as regressors. The estimated fixed effects indicate the average willingness to drive of a respondent. The figure below plots the distribution of the estimated individual fixed effects. They fall into three segments, which reflect the underlying nature of our voting survey data. Each individual faces two jobs. Thus, the respondents are likely to be separated into three groups: those who say yes to both jobs, those who say no to both jobs, and those who say yes to one of the jobs.

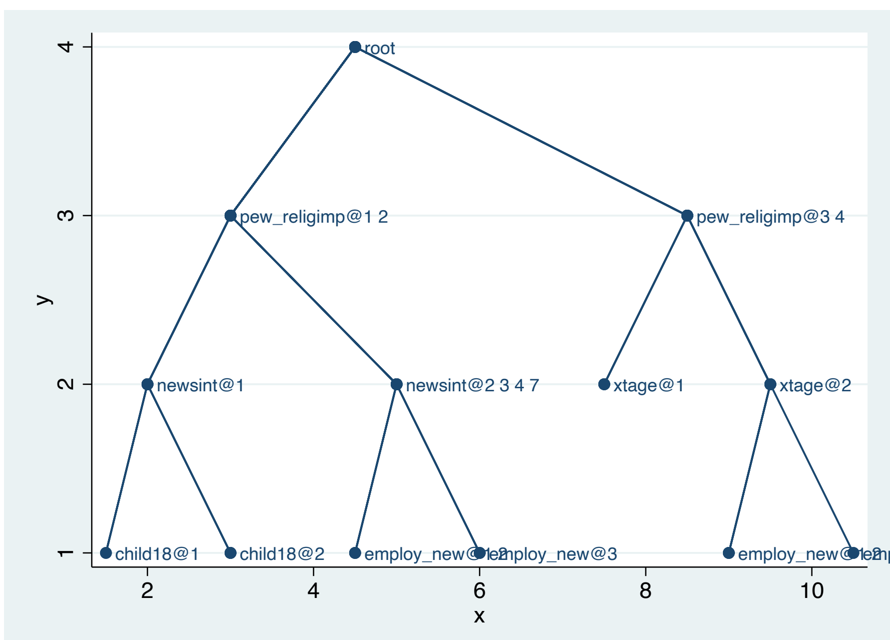
[22]Logit and random forest models produce similar error rates of 21%-23. The errors mostly come from false negatives. Our models predict few positives (around 2.4%-5%), even though the true positives are 20% of the data.

Figure A1. Distribution of individual fixed effects of willingness to drive



Because the decision tree model we use caps the number of values of the outcome variable, we segment the individual fixed effects into three categories based on the above distribution, using cut points of 0 and 0.5. The following graph shows the tree generated by the model and how the variables are split. The model uses five variables and produces seven mutually exclusive and collectively exhaustive strata.

Figure A2. Stratification generated by a decision tree model



Step 4: Estimate the distribution of different strata in a representative subpopulation of likely drivers.

Table A1 presents the seven strata created from the above step, with the definition presented in Column 1.

Table A1. Distribution of each stratum in the general population and likely driver subpopulation.

Strata	Definition of strata	Pr(YesDrive = 1)	Count	Weighted count	Distr in gen pop	Likely drivers	Distr in likely drivers	Draws
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
5	pew_religimp@3 4;xtage@2;employ_new@1 2	11%	266	263	6%	30	6%	62
7	pew_religimp@3 4;xtage@2;employ_new@3	18%	142	140	3%	25	5%	51
2	pew_religimp@3 4;xtage@1	19%	493	482	10%	90	18%	183
3	pew_religimp@1 2;newsint@2 3 4 7;employ_new@1 2	19%	425	441	10%	83	17%	169
6	pew_religimp@1 2;newsint@2 3 4 7;employ_new@3	25%	467	490	11%	123	25%	251
4	pew_religimp@1 2;newsint@1;child18@2	26%	334	327	7%	85	17%	174
1	pew_religimp@1 2;newsint@1;child18@1	35%	174	152	3%	54	11%	110
Sum			2301	2297	50%	491	100%	1000

Column 2 presents the likelihood of becoming a driver for each stratum. This variable is calculated from the raw data, by first calculating the mean(YesDrive) for each respondent based on the two job designs they face and then averaging across respondents in this stratum. The table is sorted by this probability, which ranges from 11% to 35%. This spread is sizable, and regression results show that the seven groups are jointly significant in explaining the likelihood of becoming a driver.

Column 3 is the raw count of the number of respondents in each stratum. Column 4 is the weighted counts of the number of respondents, where the weights are provided by YouGov to restore our voting survey sample to our target (general population) population.

Column 6 is the expected number of likely drivers for each stratum, which is the product of Column 2 and Column 4. Column 5 and Column 7 are, respectively, the distribution of each stratum in the general population and the likely driver subpopulation. The comparison of these two columns shows that strata that are more likely to drive are better presented in the likely driver population. Finally, the last column presents the number of respondents we draw from each stratum, which is 1000, which is our targeted sample size, multiplied by Column 7.

A3. Current and Past Driver Sample

It is difficult to survey current and past drivers systematically. One source of data is YouGov's own panel, which identifies current and past drivers by asking: Have you ever worked for any type of app-based gig work? Please select all that apply: (1) Ridesharing services (e.g., Uber, Lyft); (2) Food or package delivery (e.g., Postmates, DoorDash, Instacart, Uber Eats, Amazon Flex); and (3) Freelance work (e.g., Upwork, TaskRabbit, Thumbtack, Amazon Mechanical Turk); (4) Other types of app-based gig work; and (5) I have never done app-based gig work. Those who select option 1 will be included in the target pool of this survey. Because their number is limited, we simply draw a random sample of 550 participants.

Appendix B. Conjoint Experiment Survey Questions

Table B1: Task 1 of both surveys

B1.1: Task 1 of the voting survey

In this survey, we will ask you about the working conditions of people who drive for ride-sharing companies such as Uber or Lyft. We are particularly interested in learning what you think these conditions should be. There are no right or wrong answers. This survey is about your opinion.

Currently, many drivers at ride-sharing companies have the following working conditions:

Mode of compensation	Drivers are not paid for the wait time between rides.
Compensation	Drivers typically earn $18 per hour on the job.
Health insurance	None
Paid time off	None
Worker's compensation	None
Unemployment insurance	None
Hours	Drivers can freely choose how many hours they work each week.
Flexibility	Drivers can freely choose when they work.
Predictability	Drivers know in advance when they will work because they control their schedules.
Drive for other platforms	Drivers can drive for multiple ride-sharing companies.

In some states, citizens are asked to vote on laws that describe permissible working conditions. If you face this question, would you vote for or against this work arrangement?

- ○ Definitely vote against
- ○ Very likely vote against
- ○ Likely vote against
- ○ Not sure
- ○ Likely vote for
- ○ Very likely vote for
- ○ Definitely vote for

B1.2: Driving survey questions (the likely-driver version)

Below, we display only the questions we ask the respondents in the driving survey. The task content is the same as the voting survey displayed in Table B1.1.

How attractive do you find these working conditions?

- ◯ 1 – Not at all attractive
- ◯ 2
- ◯ 3
- ◯ 4
- ◯ 5
- ◯ 6
- ◯ 7 – Very attractive

If you considered working for a ride-sharing company at some point in your career, would you personally be willing to drive under these working conditions?

- ◯ Yes
- ◯ No

Table B2. An example of Tasks 2-7 of both surveys

B2.2. An example of Task 2 of the voting survey

In the following, we will ask you to compare the working conditions you just saw (Job A) to other working conditions (Job B). The differences between the two jobs are bolded. This is the first of 6 comparisons that we will show you.

	Job A	**Job B**
Mode of compensation	Drivers are not paid for the wait time between rides.	Drivers are not paid for the wait time between rides.
Compensation	Drivers typically earn $18 per hour on the job.	Drivers typically earn $18 per hour on the job.
Health insurance	None	**The company contributes financially to health insurance for drivers who work at least 30 hours per week.**
Paid time off	None	None
Worker's compensation	None	**Company provides workers'compensation. Workers'compensation covers the cost of work-related injuries. When drivers cannot work at all, they earn 66% of their average daily compensation during the previous quarter.**
Unemployment insurance	None	None
Hours	Drivers can freely choose how many hours they work each week.	Drivers can freely choose how many hours they work each week.
Flexibility	Drivers can freely choose when they work.	**Drivers provide their availability in 8-hour blocks. The company decides on their final schedules.**
Predictability	Drivers know in advance when they will work because they control their schedules.	**The company can change or cancel scheduled shifts, giving at least 1 days' notice.**
Drive for other platforms	Drivers can drive for multiple ride-sharing companies.	Drivers can drive for multiple ride-sharing companies.

In some states, citizens are asked to vote on laws that describe permissible working conditions. First consider Job B, would you vote for or against this work arrangement?

- ○ Definitely vote against
- ○ Very likely vote against
- ○ Likely vote against
- ○ Not sure
- ○ Likely vote for
- ○ Very likely vote for
- ○ Definitely vote for

If you had to choose between Job B and Job A, which one would you vote for?

- ○ Job A
- ○ Job B

B2.2. Driving survey questions

Below, we display only the questions we ask the respondents in Tasks 2-7 of the driving survey. The task content is the same as the voting survey displayed in Table B2.1.

How attractive do you find Job B?

- ○ 1 – Not at all attractive
- ○ 2
- ○ 3
- ○ 4
- ○ 5
- ○ 6
- ○ 7 – Very attractive

Which working conditions do you find more attractive?

- ○ Job A
- ○ Job B

If you considered working for a ride-sharing company at some point in your career, would you personally be willing to drive under the working conditions of Job B?

- ○ Yes
- ○ No

Table B3. Task 8 of the voting survey

Now, we are interested in your own willingness to drive for a ride-sharing company like Uber or Lyft. Consider the same pair of jobs you just saw:

	Job A	**Job B**
Mode of compensation	Drivers are not paid for the wait time between rides.	Drivers are not paid for the wait time between rides.
Compensation	Drivers typically earn $18 per hour on the job.	**Drivers typically earn $12 per hour on the job.**
Health insurance	None	**The company contributes financially to health insurance for drivers who work at least 20 hours per week.**
Paid time off	None	None
Worker's compensation	None	**Company provides workers'compensation. Workers'compensation covers the cost of work-related injuries. When drivers cannot work at all, they earn 66% of their average daily compensation during the previous quarter.**
Unemployment insurance	None	**Company provides unemployment insurance. Drivers earn 50% of their average daily compensation during the previous quarter for up to 26 weeks when they are unemployed.**
Hours	Drivers can freely choose how many hours they work each week.	**Drivers are required to work at least 20 hours per week.**
Flexibility	Drivers can freely choose when they work.	Drivers can freely choose when they work.
Predictability	Drivers know in advance when they will work because they control their schedules.	Drivers know in advance when they will work because they control their schedules.
Drive for other platforms	Drivers can drive for multiple ride-sharing companies.	**Drivers are not allowed to drive for other ride-sharing companies.**

If you were to consider working for a ride-sharing company at some point in your career, would you personally be willing to drive under each of the following working conditions?

	Definitely not	Very likely not	Likely not	Not sure	Likely yes	Very likely yes	Definitely yes
Job A	○	○	○	○	○	○	○
Job B	○	○	○	○	○	○	○

Table B4. Task 8 of the driving survey

Here is one of the jobs you said earlier you were willing to accept:

Mode of compensation	**Drivers are paid for every hour on the job, including the wait time.**
Compensation	**Drivers earn a fixed $30 per hour on the job.**
Health insurance	None
Paid time off	None
Worker's compensation	**Company provides workers'compensation. Workers'compensation covers the cost of work-related injuries. When drivers cannot work at all, they earn 66% of their average daily compensation during the previous quarter.**
Unemployment insurance	**Company provides unemployment insurance. Drivers earn 50% of their average daily compensation during the previous quarter for up to 26 weeks when they are unemployed.**
Hours	**Drivers are required to work at least 20 hours per week.**
Flexibility	Drivers can freely choose when they work.
Predictability	Drivers know in advance when they will work because they control their schedules.
Drive for other platforms	**Drivers are not allowed to drive for other ride-sharing companies.**

Imagine you decided to accept this job and start driving for one of the ridesharing companies.

How many hours do you think you would drive on a typical day?

In a typical week, how many days do you think you would drive for the company?

Do you expect to drive about the same number of hours each week?

- ◯ My hours would be roughly the same from week to week.
- ◯ My hours might change somewhat from week to week.
- ◯ My hours would likely be very different from week to week.

Appendix C. Power Analysis

A simple way to conduct a power analysis for a conjoint experiment is to think of it as a series of regressions involving only one dummy variable for each separate level of an attribute (Schuessler and Freitag, 2020). This is because randomly sampled individuals are matched with randomly chosen profiles. As a result, focusing on the attribute with the maximum number of levels gives us a conservative estimate of statistical power. When an attribute contains more levels, there are fewer observations available to compare each of the alternative levels to the default. When investigating interaction effects, the number of subgroups is multiplied by the number of levels of the other attribute. The sample size required to detect a given effect will increase correspondingly.

Because the sample size of our surveys is fixed, the following table lists the minimum detectable effects (MDE) for each of the surveys. The MDEs are evaluated at the 0.05 significance level (alpha) with 80% power. Because our core dependent variables are the likelihood of driving or voting, we use a chi-squared test to test two independent proportions. For simplicity, we set the baseline proportion as 0.5, which is fairly close to our pilot data whose sample means range between 0.51 to 0.66.

We provide a conservative estimate of the MDE for the job attribute that has the largest number of discrete levels in our analysis, which is four. The total effective number of observations is the number of respondents, N, multiplied by the number of unique job profiles they evaluate. Because we focus on the forced-choice data in the voter survey, there are six unique data points for each respondent. The total effective number of observations is, thus, 3000*6 = 18,000. Because the four levels are randomly distributed, the number of observations available to compare any alternative to the default value is expected to be N/4*2, with each group sharing N/4 observations.

For the driver surveys, because we primarily focus on the independent-rating data, the number of unique job profiles each respondent evaluate is seven. Thus, the total number of observations is 1000*7 = 7,000 for the likely driver survey, and 550*7 = 3,850 for the current/past driver survey. Because the respondents will always see the status-quo option, we will have more observations with default than observations with alternative values. Specifically, (N + 6*N/4) observations will assume the default value, and 6*N/4 will have an alternative value.

We also provide an estimate of the minimum detectable effect size for interacting this four-level attribute with a two-level attribute or a binary variable. In this case, we have eight different subgroups, and the number of observations will be reduced by half.

	Voter Survey	Likely Driver Survey	Current/past drivers
Uniqe number of respondents	3000	1000	550
Effective total number of observations	18000	7000	3850
An attribute with four levels			
Default group (n1)	4500	2500	1375
Alternative group (n2)	4500	1500	825
Minimum detectable effect	0.030	0.046	0.062
An attribute with four levels interacting with one with 2 levels			
Default group (n1)	2250	1250	688
Alternative group (n2)	2250	750	413
Minimum detectable effect	0.042	0.065	0.087