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# Being the Boss

## Gig Workers' Value of Flexible Work

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### Abstract

Workers who join the gig economy face a challenging trade-off. Gig work provides worktime flexibility and a sense of being one's own boss, but gig workers forgo certain protections that employees enjoy. In this paper, we study the work patterns of a large sample of drivers in the food delivery business to better understand the value of worktime flexibility. Our results indicate that the vast majority of drivers place significant value on flexibility. We then use our estimates to study how flexibility concerns, earnings considerations, and worker welfare influence the regulation of gig work. Our context is Proposition 22, a recent California ballot initiative that protects gig workers' worktime flexibility and provides an earnings guarantee. We find that counties where drivers stood to earn more from the earnings guarantee were more likely to vote in favor of Proposition 22, although this relationship disappears when factoring in political ideologies. Surprisingly, we also uncover a robust negative association between our estimates of driver surplus and support for Proposition 22. This suggests that voters and economists think about worker welfare differently, particularly in the context of gig work.

### 1. Introduction

With the advent of on-demand digital platforms, millions of workers have joined the gig economy. The U.S. Bureau of Labor Statistics estimates that 1.6 million workers—about 1% of the American labor force—complete jobs and tasks that they receive through websites or mobile apps (Bureau of Labor Statistics, 2018a). Under broader definitions of gig work, the number of persons in alternative work arrangements is even larger. For instance, 10.6 million individuals report working as independent contractors (6.9% of total employment), 2.6 million are on-call workers (1.7% of total

employment), and 1.4 million find work through temporary help agencies (0.9% of total employment) (Bureau of Labor Statistics, 2018b).

Gig work, in particular the type provided by companies that offer ride sharing, delivery, or shopping services, is both popular and controversial. Gig workers get to set their own schedule, flexibly supplement their income, and work for multiple platforms at one and the same time. In a recent survey among meal delivery workers, 76% of the 808 respondents said that flexibility was extremely important to them, and 69% highly valued the opportunity to earn extra income (Mellman, 2020).<sup>1</sup>

While millions have joined the gig economy, critics see this type of work as providing inadequate income and irregular hours. Gig workers, they point out, go without many of the protections that employees enjoy (Berins Collier, Dubal and Carter, 2017). Because gig workers are legally classified as independent contractors, they lack minimum wage, overtime, and paid leave protections; they are not entitled to unemployment insurance, workers' compensation, social security and Medicare benefits; they enjoy fewer legal protections against discrimination and harassment; and they do not have the right to unionize (Valerio, 2016).<sup>2</sup> While the formal legal differences between independent contractors and employees are stark, the actual benefits of attaining employee status are more modest for many gig workers because they work too few hours to fully qualify for employment protections. For instance, in our dataset of drivers in California, only about 45% of drivers would have qualified for unemployment compensation if they had applied for benefits in the fall of 2020.<sup>3</sup> In other instances, limited work hours substantially reduce the benefits that come with employee status. For example, the average driver in our dataset would only earn about 20 minutes of paid sick leave each week under current California rules.

Our paper makes two contributions. First, we provide estimates of the value of worktime flexibility for an important segment of the gig economy, meal-delivery services. To gauge the value of

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<sup>1</sup> The survey was commissioned by DoorDash and conducted by the Mellman Group. The 808 respondents did not learn the name of the sponsor.

<sup>2</sup> The difficulties of extending traditional protections such as hours-based benefits to gig workers are discussed in Harris and Krueger (2015).

<sup>3</sup> This calculation is based on 138,531 drivers who enter our dataset before October 2019. We ask how many of them would qualify for unemployment benefits if they applied for support in the 3<sup>rd</sup> quarter of 2020. To be eligible, California requires an income of at least \$1,300 in one of the last five quarters. We also take into account alternate ways to qualify for support. Note that 45% is a lower-bound estimate because we only observe a driver's income from DoorDash. Drivers who work for multiple platforms are more likely to qualify than our analysis suggests.

setting one's own schedule, we estimate compensating earnings differentials and reservation wages. We find that flexibility has a substantial impact on worker welfare. Forcing the average driver out of their preferred shift is equivalent to cutting weekly earnings by 5.3%. We also document substantial heterogeneity, both with respect to the overall value of flexibility and the welfare consequences of different types of flexibility. For more than 20% of our drivers, flexibility is of modest value. For the top decile, losing flexibility is equivalent to a 15% pay cut. Looking at different types of flexibility, our results suggest that the ability to start or stop working at any moment and the flexibility to change hours from week to week are particularly valuable for the drivers in California.

A second contribution of our paper concerns the political economy of labor regulations. Perhaps the most prominent legislative initiative to re-classify gig workers as employees is California's Assembly Bill 5 (AB5), which went into effect on January 1, 2020 (California Legislative Information, 2019). The law required gig-economy transportation (Uber, Lyft) and delivery services (DoorDash, GrubHub) to classify their drivers as employees (Superior Court, 2020). In response, five companies—DoorDash, Lyft, Uber, Instacart and Postmates—supported a ballot initiative, Proposition 22 (Prop 22), that created an exception for app-based transportation and delivery companies. The initiative passed with 58% of the vote in November 2020.

Applying our estimates, we are able to measure the extent to which the value of worktime flexibility influenced California voters. The initiative is particularly interesting because it introduced an earnings guarantee *and* preserved worktime flexibility, allowing us to see how concerns about gig workers' earnings and welfare shape labor market regulations. The biggest predictor of a county's support of Prop 22 was its share of registered Republican voters, indicating that political ideology drove much of voters' decisions. However, we find evidence that counties in which drivers stood to gain more from the earnings guarantee were more supportive of Proposition 22, which suggests that voters do take the welfare of drivers into account. Quite surprisingly, we find the opposite relationship for worktime flexibility. Counties where drivers earned greater rents from DoorDash were less supportive of Prop 22. One explanation for this result is that workers with low reservation wages, whom we see as placing a high value on flexibility, are perceived as particularly vulnerable by the voters. We present evidence that this may have occurred in this setting.

Our paper is related to three strands in the literature. A first is concerned with estimating the wage elasticity of labor supply (for reviews, see Killingsworth and Heckman 1986; Pencavel 1986;

Blundell and Ma-Curdy 1999.) A challenge in many of these studies is that workers are not free to choose their own hours. In response, scholars turned to settings in which workers have greater control. Camerer et al. (1997) studied New York City cab drivers, Oettinger (1999) stadium vendors, Fehr and Goette (2002) bike messengers, and Chou (2000) and Farber (2005, 2015) revisited the question of how taxi drivers choose their hours. The findings were mixed. Camerer et al.'s (1997) analysis suggests that taxi drivers target a specific level of earnings. Once they hit that target, they quit for the day. By contrast, Farber (2005, 2015) finds a positive elasticity of labor supply and no evidence of a target income. In our setting, drivers arguably face even smaller constraints than taxi drivers who need to be concerned with medallions, taxi leasing periods, multiple drivers using the same car, and a plethora of regulations. By contrast, DoorDash drivers are at liberty to choose their preferred number of hours.

Our work is also related to the nascent literature on the value of workplace flexibility. We know from surveys that many individuals have a preference for flexible work arrangements (Dean and Auerbach, 2018). But we are aware of only a few studies that estimate a monetary value of flexibility. Mas and Pallais (2017) conduct a discrete-choice experiment with applicants for a position in a call center. They find that the average applicant places little value on overall flexibility. While most applicants would not accept a pay cut in exchange for the ability to set their own schedules, the top 25 percent of workers are willing to give up at least 10 percent of their wages to be able to make their own schedule. Many applicants were willing to accept a substantial pay-cut to avoid evening and weekend work. Our contribution is closest to Chen et al. (2019) who study the value of flexibility for Uber drivers. They find that the drivers place a high value on flexibility. The difference in value between Uber and fixed taxi shifts is estimated to be \$135 per week. In other words, flexibility creates as much value as driving 6.7 hours. Our paper replicates the Chen et al. study and its use of an MCMC algorithm to compare the value of flexibility in a market with very different dynamics than the market for ride sharing.

Finally, we build on earlier work on the economics of regulation (Stigler, 1971) and non-market strategy (Baron 1995) to shed light on ways that firms can influence their business environment (JM De Figueiredo et al., 2016). This aspect of our work speaks to the literature on corporate political activity (CPA), the corporate attempts to shape government policy in ways favorable to the firm (Hillman et al. 1994). To our knowledge, we are one of the first papers in non-market strategy to directly examine how firms shape the regulation of labor markets. Ramirez and Tarzijan (2018) have

touched upon this idea in studying how employees appropriate value from the firm (Garcia-Castro et al., 2015), however they take the regulatory environment as outside the firm’s control. The gig economy/platform setting is an optimal one in which to study this topic because the environment is still being shaped and opposition exists due to concerns that workers are not sufficiently protected (Ricart et al., 2020). Finally, while much of the literature on CPA is focused on firm lobbying efforts, our study examines a setting in which a firm goes “directly to the people” in the form of a ballot initiative. There is evidence that policies enacted by initiatives are more in line with majority opinion than legislation (Matusaka, 2018), so there may be important differences in how firms appeal to public opinion as opposed to appealing to regulators.

## **2. The Nature of Gig Work**

Gig work is fairly new and not particularly well understood. We begin by describing the principal work choices that the drivers in our sample make. Our data come from DoorDash, a delivery platform company founded in Palo Alto in 2013. With a market share of 50%, the company now leads on-demand food delivery from restaurants in the United States (Yeo, 2020).

The company shared data for all its drivers in California starting from February 1, 2019 to August 1, 2020.<sup>4</sup> We observe 426,385 DoorDash drivers working 27 million “shifts”. In the terminology that we will use, a shift begins when a driver logs into the DoorDash app and begins to receive offers for delivery work. It ends when the driver logs out. Working on the DoorDash platform, drivers are free to accept or ignore offers the company sends and make frequent use of the right to decline work. Thus, to generate our sample, we include only shifts in which at least one delivery was completed. The typical shift of this nature is quite short, just over two hours. A delivery starts when the driver accepts an offer and ends when the driver confirms in the app that the meal has been delivered to the customer. The time spent making deliveries is a driver’s “engaged time” (see Table 1 for summary statistics). It includes the time driving to the restaurant, waiting for the meal to be ready, and driving to the customer. The difference between shift time and engaged time consists of time spent waiting

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<sup>4</sup> However, statistics in this section and in section 3 use data from February 1, 2019 – June 30, 2020 to avoid picking up the inflow of new drivers in July 2020 resulting from DoorDash’s integration of Caviar.

for offers, breaks, work for competing delivery companies, and private errands. In surveys, about half of DoorDash drivers report that they work for multiple companies (Mellman, 2020).

In the weeks in which they work (i.e. active weeks), the typical driver in California works 3.4 days a week for a total of 9.1 hours of engaged time. Consistent with the survey data on the importance of part-time work (Campbell, 2018), 50% of drivers spend less than 6 hours per active week making deliveries.<sup>5</sup> This is an interesting difference from Uber drivers who work much longer hours, about 15 hours a week in the case of the median driver (Hall and Krueger, 2018).<sup>6</sup> DoorDash drivers earn \$187.51 in these weeks on average, or \$20.33 per hour of engaged time. These hourly earnings include tips, but exclude payments from DoorDash for customer cancellations or volume-based bonuses.<sup>7</sup>

It is interesting to see how work evolved during the 2020 pandemic. Comparing March through June 2020 to the same period in 2019, drivers drove about the same number of days (3.62 vs. 3.23 per week) but they worked longer hours (10.45 vs. 8.55) and earned more money (\$242 vs. \$150) as a result (see Table 2a). This is consistent with a recent survey in which almost half of all drivers say that they or a family member lost a job during the pandemic and that they work longer hours to make up the difference (Mellman, 2020). A potential difficulty with the data in Table 2a is that they might reflect DoorDash's growth. To separate changes over time from the effect of COVID-19, we estimate models that include polynomial time trends (Table 2b). The coefficient of interest is the indicator variable that denotes the change from March to June 2019, the omitted period, to the same period in 2020. Comparing the same months removes concerns over seasonal effects, and the flexible time trend captures overall business growth. The results indicate that the increase in days worked, engaged time and weekly earnings do not reflect a general time trend. In fact, these variables all declined significantly from March-July 2019 to August-February 2020. During the pandemic, drivers increased

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<sup>5</sup> In the meal delivery survey, 30% of respondents reported doing gig work "when they have extra time." Another 25% said they provide gig services when they "need extra income." Only 16% of respondents looked to gig work as their main source of income. Another 24% regarded it as a "steady source of earnings." These responses are similar to earlier research findings (Farrell and Greig, 2017).

<sup>6</sup> Note that this can only be compared roughly with our statistics which are in terms of engaged hours in active weeks. Hall and Kreuger use all time logged into the Uber app, conditional on the driver completing four trips in a given month.

<sup>7</sup> These are a lower bound on gross earnings, as they exclude payments from DoorDash for customer cancellations or volume-based bonuses. However as is typical for gig workers, DoorDash drivers are not reimbursed for their driving expenses, such as gasoline, maintenance, depreciation, or insurance. Using Hyman et al. (2020)'s estimate of marginal costs as \$0.19 per mile for ride-hailing platforms, the average DoorDash driver's cost of driving would be \$2.17 per engaged hour.



their engagement significantly. They added 0.26 days per week, worked an extra 2.4 hours per shift, and earned an additional \$39.50 per week, a 26% increase over the pre-pandemic period. This suggests that the ability to scale working hours up or down in response to some macro-economic shocks is an important benefit for gig workers.

### 3. Understanding Work Patterns

An important benefit of gig work is its flexibility. Many individuals combine gig work with other jobs. For instance, about two thirds of Uber drivers work either full-time or part-time on another job (Hall and Krueger, 2018). Similarly, 39% of DoorDash drivers hold a full-time job, 14% work part-time, and 20% are students. 14% report being self-employed. For only 16% of drivers is gig work their only occupation (Mellman, 2020). The ability to choose work hours provides two types of benefits. Drivers can select hours that are particularly attractive, for instance times that are compatible with their main job or hours when meal-delivery compensation is particularly attractive. Like many on-demand platforms, DoorDash balances supply and demand by offering drivers “peak pay” during busy hours. Of the 100 million deliveries that we observe in our data, roughly 30% profited from peak pay. Conversely, drivers benefit from flexibility by not having to work when it is inconvenient for them. 11% of DoorDash drivers are stay-at-home parents, many of whom want to be back home when the children return from school. Similarly, students will want to schedule dashing around class schedules.

#### a. Choosing Shifts and Shift Length

To better understand drivers’ work patterns and assess the value of flexibility, we first want to understand when and for how long DoorDash drivers remain engaged. We follow the literature on taxi drivers (Camerer et al. 1997, Farber 2005) and estimate how earnings (measured as pay per minute) and time fixed effects influence the willingness of workers to drive:

$$(1) \quad H_{it} = \eta w_{it} + \alpha_i + \gamma_{it} + \varepsilon_{it}$$

In (1),  $H_{it}$  is the number of engaged minutes driver  $i$  works in a shift at time  $t$ . The driver earns average wage  $w_{it}$  over a shift.<sup>8</sup>  $\eta$  is the estimated elasticity of labor supply. The model includes driver

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<sup>8</sup>  $w_{it}$  is defined as total earnings over the shift divided by  $H_{it}$  multiplied by 60, which is the hourly wage (engaged time).

( $\alpha_i$ ) and time ( $\gamma_{it}$ ) fixed effects which we implement as indicator variables for 12 blocks of time.<sup>9</sup> We allow the time fixed effects to vary by driver, taking into account that the desirability of work hours is highly personal.

Table 3 provides the basic results of this model. Column (a) includes driver and time fixed effects. Column (b) allows the time fixed effects to vary by driver. To ensure we have enough data to infer drivers' preferences, we consider only drivers who have worked at least once per week in 16 or more of the 52 weeks between August 2019 and July 2020.<sup>10</sup> There are 65,597 drivers in California who fit this definition, and we refer to this subset as "committed drivers". These drivers spend an average of 11.3 engaged hours per active week making deliveries for DoorDash, compared to 9.1 hours per week for the average California driver profiled in Table 1. To generate our estimates of the value of flexibility, we consider driving patterns from August 2019 through July 2020 only. Within this panel, committed drivers have a mean duration of 28 weeks.

A conceptual difficulty with the results in the first two columns of Table 3 is what Camerer et al. (1997) call the "division problem," the fact that hours worked appears in the calculation of wages and on the left-hand side of (1), leading to a negative bias in the estimation of  $\eta$ . Camerer et al. (1997) used market-level wages as an instrument to correct the bias. We use the occurrence of "peak pay" during the shift as our instrument. The instrument is valid if it is correlated with  $w_{it}$  and if it satisfies the exclusion restriction. If the division bias mainly reflects measurement error and if the error is uncorrelated across drivers, peak pay is a valid instrument.

Columns (c) and (d) provide first and second-stage estimates. The use of peak pay as an instrument changes the estimate dramatically. In regressions (a) and (b), the elasticity of labor supply is estimated to be negative. But once we instrument wage with peak pay in regression (d), our estimate of  $\eta$  becomes positive. To be specific, we estimate that a \$1 increase in the average wage during a shift is associated with an additional 6 minutes of engaged dashing time. Using these

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<sup>9</sup> Following the method used in Chen et al. 2019, we group hours into blocks that are associated with a common shift in the labor supply and encompass distinct meal-times. Shifts are associated with the block in which they begin. Details on the timeframes of blocks can be found in the note of Table 5.

<sup>10</sup> In line with Chen et al. (2019), we consider a driver to be working in a week if they spend at least 10 minutes of a single hour in that week on a delivery. To generate this, we transform the dataset into discrete hours (168 per week), and track the driver's engaged time in each hour. We remove 21 days from our sample, such as Labor Day and Christmas, in which drivers may radically depart from their typical driving patterns.

compensating differentials, we can then calculate the dollar value of asking the drivers to work at different times via  $\gamma_{it}$ .

**b. Reservation Wage Model of Driver Engagement**

A more direct way of examining drivers’ preferences over shift times is to estimate their reservation wages over the hours that they are engaged in delivery work. Following Chen et al. (2019), we estimate a multivariate probit model:

$$(2) \quad y_{it}^* = w_{it}^* - w_{it} = \mu_i(t) - w_{it} + \varepsilon_{it}$$

$$Y_{it} = \begin{cases} 1 & \text{if } y_{it}^* > 0 \\ 0 & \text{if } y_{it}^* \leq 0 \end{cases}$$

$y_{it}^*$  is a latent variable whose sign we observe.  $w_{it}^*$  is driver  $i$ ’s reservation wage at time  $t$ .  $\mu_i$  is the mean reservation wage which varies with our 12 time blocks.  $w_{it}$  is the wage that drivers observe when they decide to accept a delivery. With each delivery that it offers, DoorDash provides drivers with the minimum expected pay—tips are extra—and driving distance. Drivers accept the delivery if the expected wage  $w_{it}$  exceeds the reservation wage  $w_{it}^*$ . While a driver’s reservation wage at any single moment can vary widely, the driver’s patterns of driving across time allow us to estimate the 12  $\mu_i$  terms. We do this by using a Markov Chain Monte Carlo (MCMC) algorithm to generate a distribution of possible estimates for each block. In each block, the algorithm samples from a normal distribution truncated from below by 0 and above at  $w_{it}$  if the driver works. If he does not, we sample from a normal distribution truncated from below at  $w_{it}$ . We use these parameter draws to estimate the mean reservation wage  $\mu_i$  as well as  $\sigma_{week}$ ,  $\sigma_{day}$ , and  $\sigma_{hour}$ , which represent the driver’s typical weekly, daily, and hourly shocks to his reservation wage.

To understand the intuition behind this method, imagine a driver who is present in our panel for four weeks. In the first two of those weeks, she drove on Sunday between 12-1pm. In the first week, her expected wage that hour was \$25, and in the second week it was \$20. In the third week, she drove earlier that day, but did not drive between 12-1pm when the city wage for that hour was \$15. In the fourth week, she did not drive at all on Sunday. For the first two weeks, the algorithm would pick a reservation wage below the expected wage (let’s say it selects \$20 and \$15 respectively). In the third week, the assumption is that the driver was available to work during 12-1pm, knew the expected wage of \$15, and decided not to work. So, the algorithm would pick a reservation wage above \$15 (say \$20).

In the fourth week, we presume that the driver was not available to work at all, so this week is ignored. Averaging the three reservation wages together would give an estimate of \$18 as the driver's mean reservation wage for the Sunday 12-1pm period. The MCMC procedure repeats this process many times to create a distribution of possible estimates.

We estimate driver reservation wages for 63,497 committed drivers.<sup>11</sup> We consider a driver to be working in an hour if she spends 10 or more minutes of that hour on a delivery. We use pay per hour of engaged time as the expected wage if the driver works and the average pay per engaged time in the driver's modal city that week if she does not work.<sup>12</sup>

Figure 1 displays the mean distribution of reservation wages for 100 randomly selected drivers in San Francisco during the Tuesday dinner (5-9pm) block. The dots are the drivers' mean reservation wages for the broader weekday dinner block. The 52 horizontal lines show the expected wage between 5-9pm in San Francisco for each week of the data, which varies between \$20-30 per hour of engaged time.

#### **4. Valuing Worktime Flexibility**

Armed with information about driving histories and drivers' reservation wages, we can now estimate the value of worktime flexibility. To make these calculations, we compare drivers' current schedules with a schedule that is controlled by their employer. Of course, we do not know how DoorDash (and other on-demand platforms) would respond to drivers being classified as employees. Laws like AB5 do not *require* companies to set fixed schedules (Sachs, 2015). But looking at other sectors of the economy with significant fluctuations in demand—restaurants and taxi companies, for instance—it appears unlikely that app-based businesses would continue to allow drivers to drop in and out of work at will and without notice. In fact, if retailers are an indication of how schedules would be set, drivers would bear a significant fraction of the cost of fluctuations in demand. In retail, 80% of part-time employees report having hours that change from week to week at the discretion of their

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<sup>11</sup> While we started with 65,597 committed drivers, around 2,000 never drove on a particular day of the week. We removed these drivers from the sample.

<sup>12</sup> DoorDash drivers see a minimum guaranteed payment, as well as estimated duration, for each offer they receive, so we use this as the measure of expected wage. If these estimates are nonsensical due to likely database errors, we use the actual payout and duration.

employers. The variation in hours is substantial. Swings of 40% in average work hours are typical. Moreover, more than one-third of retail workers know their schedules a week or less in advance, making any sort of planning difficult (Williams et al.).

In our simulations, we take two approaches to worker schedules. The first is a “gentle” approach. We explore how worker surplus changes when the driver is no longer able to work in their preferred block and is instead required to work those same hours in a different block. All other driving decisions are left intact. The second is a more “heavy-handed” approach, in which the driver must work all their hours in a single block. In both situations, the company respects the total hours of labor that the driver chooses to supply. However, the degree of control that the company has over the timing of shifts differs dramatically—and gives us bounds on the value of flexibility. Finally, we look at the direct estimate of expected surplus from flexibility using the estimated reservation wages and variance components, and see how these results compare.

### Compensating Differentials

In order to calculate the value of the DoorDash arrangement compared to less-preferred shifts, we use estimates of  $\eta_i$  and  $\gamma_{it}$  from a modified version of (1) that allows the labor elasticity to vary by driver. Using this modified IV specification, we find that  $\eta_i > 0$  for 80% of committed drivers. It is for these 51,231 drivers that we calculate the required compensation to work at less-convenient hours. We express compensation as a fraction of a worker’s weekly earnings.

Panel a of Table 4 reports summary statistics for all 12 blocks. Moving the median driver from his preferred block to another shift is equivalent to cutting his weekly earnings by 2.9%. Flexibility is twice as valuable for the average driver. The difference between median and mean values reflects the behavior of a subset of drivers who place a very high value on flexibility. For the top 10%, not being able to drive their preferred shift is like cutting their weekly pay by 17%. A worst-case scenario for these drivers is to be asked to work the 3am to 7am shift. This is equivalent to cutting their weekly pay by 23.8%. Panel b of Table 4 scales up this approach by asking how much we would have to compensate drivers if they could no longer work their top 2 preferred blocks of time. Not surprisingly, this work assignment requires even greater compensation than a schedule that excludes only their preferred block of time. Take the typical driver and ask him to work at night (Table 4, last row). To make him indifferent between his top 2 driving times and a night shift requires a payment of 10.2% of the person’s weekly earnings.

Table 5 reports the results for the heavy-handed approach. In this scenario, we force drivers to work every shift they drive in only one block.<sup>13</sup> We find that assigning them to the shift they drive the least often is equivalent to a 24.0% pay cut for the median driver and a 36.9% pay cut for the average driver. Even more extreme, requiring drivers to work all their time in their least-preferred block is like reducing their weekly pay by 57.4%. These compensating differentials are large, pointing to the substantial value of being able to choose work times.

### Reservation Wages

We use the estimated reservation wages to calculate driver surplus and changes in surplus if the drivers lose worktime flexibility. Table 6 provides these results. We find that the mean driver receives a surplus of 40.4% of weekly earnings. We begin restricting drivers' flexibility by requiring them to commit to shifts the week before (scenario A). We estimate that we would need to give the mean driver 29.3% of his weekly pay to make up for the reduction in flexibility. The approximately 70% decrease in surplus is striking, but consistent with earlier results for Uber drivers (Chen et al., 2019). When we ask drivers to commit to shifts the day prior (scenario B), the drop in surplus is close, but not quite as large. That is to say, once drivers can choose shifts a week in advance, much of their desire to choose workhours is met. The drivers appreciate having daily flexibility as well, but it does not add that much. The value of flexibility in the gig economy, our estimates suggest, comes not just from choosing preferred times to work in general, but from the ability to be inconsistent from hour to hour.

Scenarios C through F in Table 6 present estimates for the four heavy-handed scheduling regimes. For these calculations, we depart from the assumption made in Table 5 that the driver works their full labor supply in that block. Instead, we ask what would occur if the company offered drivers a strict assignment of hours. The driver would be required to drive all hours of a block (e.g. every Mon-Thurs 5-9pm) and cannot pick up shifts at other times. In this model, drivers continue to choose how many days they want to work but the shift is given. Drivers can lose out in two ways from these strict assignment. First, they lose the ability to work outside of these assigned times, even during hours in which the market wage exceeds their reservation wage. Second, they may be forced to drive hours in

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<sup>13</sup> This ignores demand-side constraints, as well as the fact that some drivers work more hours in a week than can fit into one block. While unrealistic, this exercise still illuminates how drivers would be affected if all of their labor supply was under the company's control, and can be compared with the results in Table 7.

which their reservation wage exceeds expected earnings. Using drivers' mean reservation wages  $\mu_i(t)$ , we find significant losses in welfare even if the drivers are assigned to the block they drive most often. We would have to compensate the mean driver 22.0% of his weekly earnings to accept this shift. This value increases to 37.6% if we assign the driver to the least-frequently driven block of time.

If the worker anticipates that the arrangement is worse than other opportunities in the market—a negative surplus—they would choose not to work for DoorDash. The number of drivers who would drop out are presented in the final column of Table 6. Requiring drivers to commit to a schedule the day prior has the smallest effect. Only 5.3% of drivers would choose other work (or leisure.) By contrast, if DoorDash assigned them to the most-frequently driven block, over 30% of workers would leave. More than 80% would choose other work if they were assigned to the least-preferred block.<sup>14</sup>

Comparing results based on reservation wages with the compensating differentials from Table 5 provides ranges for the value of flexibility. Asking the mean driver to work his least-frequently driven block, the estimated surplus reduction is nearly the same between the two methods. While this is not an apples-to-apples comparison for many reasons,<sup>15</sup> the fact that both methods give estimates in the same ballpark for all of the scenarios provides some confidence in our estimates.

Lastly, we examine how the valuation of flexibility for committed drivers differs depending on how many engaged hours they tend to work. Table 7 displays the estimated compensation required for scenarios A, D, and F to the mean driver in each strata. Using scenarios A and D as benchmarks, the value of flexibility per hour declines monotonically with the number of hours worked per week.<sup>16</sup> For the small number of drivers that work more than half-time on DoorDash, flexibility is not as valuable because there is comparatively less room left in their schedule. However, even those driving 30+ engaged hours per week would need compensation worth 20% of their weekly earnings to move to scenarios A or D.

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<sup>14</sup> Least-preferred is the block with the highest mean reservation wage.

<sup>15</sup> In addition to the different assumptions about the total number of hours worked per driver, the fixed-effect estimates use a subset of the 63,497 drivers used in the MCMC analysis.

<sup>16</sup> There is some variation depending on which benchmark is used. Using scenario E, the value of flexibility appears consistent across the strata of hours worked per week.

## 5. The Political Economy of Gig Work Regulations

The financial performance and perhaps even the viability of on-demand platforms depends on the regulatory framework under which they operate. From their early days, companies like Uber pursued non-market strategies that were designed to defend the firm's freedom to operate (Baron 2016). California's Assembly Bill 5 (AB5) constituted a direct challenge to the current operating model of app-based transportation and delivery companies. Building on an earlier court decision (*Dynamex Operations West Inc. v. Superior Court of Los Angeles*, 2018), the law required companies to assume that their workers were employees unless they met three conditions, known as the "ABC" test: the workers must be free to perform services without being controlled by the company; the workers have to perform tasks that are outside the company's usual activities; and they need to be customarily engaged in the business in question. In an early test case, California Superior Court Judge Ethan Schulman ordered the ride-sharing companies Uber and Lyft to reclassify their contract drivers as employees, noting that "drivers are central, not tangential, to Uber and Lyft's entire ride-hailing business" (Superior Court, 2020).<sup>17</sup>

In response, five app-based companies—DoorDash, Lyft, Uber, Instacart and Postmates—supported a ballot initiative that would exempt them from having to re-classify their drivers as employees. The initiative, Proposition 22, sought to strike a balance between AB5 and a situation in which gig workers enjoy little protection. Writing in the *New York Times*, Uber CEO Dara Khosrowshahi argued, "Our current employment system is outdated and unfair. It forces every worker to choose between being an employee with more benefits but less flexibility, or an independent contractor with more flexibility but almost no safety net" (Khosrowshahi, 2020). Tony Xu, CEO of DoorDash, said, "Instead of getting caught in the no-win dichotomy of employment versus independent contracting, we need a third way that recognizes that this new approach to work is here to stay. And that's because workers want it and it provides the legal protections and benefits they deserve—it's as simple as that."

Under Prop 22, 2020, app-based transportation and delivery companies pay their drivers a minimum of 120% of the local minimum wage plus 30 cents per mile during work trips. For drivers

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<sup>17</sup> While AB5 could potentially impact more than 1 million workers in California, the law exempted more than 50 types of businesses and professions, including insurance agents, attorneys, real estate agents, as well as referral agencies (Bertram and Blum, 2019; Lake, 2020). A new law passed in September 2020, provided additional exemptions for B2B transactions, professional services, and specific occupations as varied as sports coaches, photographers, and pool cleaners (Micheli, 2020; Myers, 2020). AB5's provisions continued to apply, however, to on-demand platforms.



who average at least 25 hours per week, the platforms provide healthcare subsidies equal to 82% of the premium for California Covered, the state’s healthcare plan.<sup>18</sup> For drivers who average between 15 and 25 hours, the subsidy drops to 41%.<sup>19</sup> The companies also provide occupational accident and accidental death insurance. Drivers continue to freely select working hours, and Prop 22 protects their right to work for competing on-demand platforms (California Official Voter Information Guide, 2020).

#### **a. Earnings Guarantee**

We use our estimates of worker reservations wages and surplus as well as the value of the Prop 22 earnings guarantee to see how these stipulations influenced the political support of Prop 22. For each driver, we apply the 2021 minimum wage to calculate the value of the earnings guarantee. The minimum wage stands at an average of \$14.40 for the state as a whole, ranging from \$14 in cities like San Diego and Santa Barbara to \$16.07 in San Francisco and Oakland.<sup>20</sup> For each of our drivers, we know how long they took to complete each delivery and how many miles they drove. Following the method described in Prop 22, we find that the average driver’s earnings would have been \$24.20 per hour of engaged time, an increase of 19%. By design, the earnings guarantee is most valuable for drivers who earn the lowest wages (Table 8). Under Prop 22 rules, the earnings of the bottom 10% would have increased by 70% to \$20.07 per hour of engaged time.

It is interesting to examine the earnings guarantee by the number of hours worked per week. Figure 2 presents a binned scatterplot of the wage increase for the sample of 65,597 committed drivers. This is shown on a per-hour rather than per-week basis in order to allow comparisons between drivers who work different numbers of hours per week. The earnings guarantee helps all drivers, although the boost is smaller for drivers who work longer hours. Those who spend between 5 and 10 hours a week completing deliveries would see an average increase of \$2.77 in their hourly wage, while those working 25+ engaged hours per week would see an increase of about \$1.75. This is a reflection

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<sup>18</sup> The subsidy is equivalent to the employer contribution for employee healthcare under the Affordable Care Act (“Obamacare”).

<sup>19</sup> However, since drivers can work for multiple platforms, they may receive subsidies from more than one company.

<sup>20</sup> The source of minimum wage data is The Economic Policy Institute (2020).

of the fact that drivers who drive more hours per week tend to generate higher earnings on a per-hour basis.

#### **b. Political Support**

Proposition 22 was supported by 58% of California voters, ranging from 40.49% in San Francisco to 70.34% in Sutter County (Secretary of State, 2021). We correlate the county-level support of Prop 22 with three groups of variables: our estimates of driver surplus and reservation wages, measures of political ideology and engagement (share of registered Republican voters and voter turnout for Prop 22), as well as county-level control variables including population characteristics and the number of restaurants in the county. See Table 9 for county-level summary statistics and a description of the sources for the control variables.

We present the basic correlations in Table 10. We find in models (1) and (2) that more sparsely populated and more racially diverse counties showed greater support for Prop 22. This latter result is in line with polling by EMC Research in November 2020, which found that the majority of Black, Hispanic, and Asian voters supported Prop 22 (Yes on Prop 22 Coalition, 2020). The number of restaurants in a county, which proxies for opportunities to have meals delivered, had no discernable impact. Our ideological variables are of critical importance. A one standard deviation increase in the share of registered Republican voters is associated with an 8.2 percentage point increase in the share of voters who favored Prop 22. Similarly, a one standard deviation increase in voter turnout is correlated with a 2.8 percentage point increase in positive votes. DoorDash drivers' wages are positively linked to support for the initiative as well. Perhaps surprisingly, our estimate of driver surplus bears a negative sign; counties where drivers earned greater rents were more skeptical about Prop 22.

To better understand this latter result, we account directly for driver reservation wages and estimate models (3) and (4) for working periods and (5) and (6) for non-working periods. You will recall that worktime flexibility creates value by allowing drivers to drive when it is particularly attractive and to pursue other activities when their expected surplus is low. Distinguishing work and non-work periods allows us to see whether the type of flexibility is associated with political support. In models (3) and (4), we see that higher reservation wages while working are negatively related to electoral

support of the initiative, as would be expected. Yet in models (5) and (6), we find that higher reservation wages while *not* working are also negatively related to electoral support of the initiative. Because drivers with higher-value leisure times would get more surplus from being able to choose their leisure hours, this is consistent with the earlier result for the overall driver surplus. One possible reason for these inconsistencies is the fact that Table 10 shows correlations, not causations. The heterogeneity in mean reservation wages across counties may be correlated with other factors that would make a levels-based analysis hard to interpret. For example, DoorDash drivers in Los Angeles County might avoid dashing during rush hour, but bad traffic may not be as relevant to drivers in San Diego County. This would mechanically make mean reservation wages in Los Angeles higher than those in San Diego, but this does not necessarily mean those drivers derive higher value from flexibility.

We can address some of these issues by looking at changes in surplus and mean reservation wages. This way, any county-specific factors will be netted out – and we can more closely study how the Prop 22 stipulations are correlated with voter support. To accomplish this, we replace driver wages for the average change in weekly earnings from the Prop 22 earnings guarantee. These results are shown in Table 11. We first use our estimates of the change in surplus compared to an arrangement that requires drivers to commit to their schedule the week prior (Table 6, scenario A) and link this change to variation in electoral support. The gains in driver earnings are positively related to voter approval in model (1), but the association disappears when we control for ideology and turnout in model (2). County population characteristics and our ideological variables retain their statistical and economic association with support for Prop 22. As in the earlier models, we find—surprisingly—that our measure of driver surplus is negatively related to voter approval. Counties with drivers who earn a greater surplus from flexibility are more reluctant to support the initiative.

As before, we can shed light on this latter result by looking at changes in reservation wages and by separating work and non-work periods. In models (3) and (4) of Table 11, we compare working and non-working reservation wages that result from assigning the drivers to their least-preferred block of worktime (Table 6, scenario F) to their actual working and non-working reservation wages. In other words, we assign drivers to their least-preferred shift and ask how reservation wages would change if

they could freely schedule their work.<sup>21</sup> On average, flexibility would lower reservation wages by \$17 (Table 9). Counties where the decline in reservation wages is smaller are more supportive of Prop 22. What can possibly explain this surprising association? One conjecture is that voters and economists think differently about reservation wages. To an economist, allocating work hours to drivers with particularly low reservation wages is desirable because the allocation creates the greatest welfare gains. By contrast, a skeptical public sees in low reservation wages a dearth of outside opportunities, making this allocation less appropriate.

In models (5) and (6), we study how flexibility from choosing non-working hours relates to political support. Analogous to models (3) and (4), we compare reservation wages when the drivers cannot take time off during block F with the higher reservation wages when they choose schedules freely. On average, reservation wages increase by \$2.48. This occurs because drivers can choose not to work in times when they have particularly high reservation wages, driving up the average non-working reservation wage. Thus, this represents an increase in driver welfare. However, as in our earlier results, this increase in driver surplus is associated with a decrease in voter support. Taken together, the results in tables 10 and 11 point to the possibility that voters and economists think about driver welfare and the desirability of gig work regulations very differently.

## **6. Conclusions**

In this paper, we use a large sample of driver work schedules to estimate the value of workhour flexibility. To do so, we follow two approaches. We use data on the timing and length of observed work hours to estimate compensating differentials for driving during specific blocks of time. To reduce “division bias,” we employ driver incentives as our instrument. In a second approach, we estimate driver reservation wages directly in a multivariate probit model.

Three findings stand out from these estimations: First, assigning drivers to specific shifts significantly reduces their welfare, even if we keep the number of hours worked unchanged. Second, there is substantial heterogeneity in drivers’ value of worktime flexibility. For many drivers, a

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<sup>21</sup> We cannot do this exercise starting from the requirement that drivers commit the week before because the calculation of surplus in Table 6 scenario A relies on the variance terms, rather than on hour-by-hour strict assignments of work.

significant fraction of their surplus from gig work vanishes if we rob them of flexibility. Third, we identify at least three types of flexibility, each of which contributes substantially to driver welfare: the ability to adopt different schedules from week to week, an option to make last-minute (hourly) changes to one's schedule, and the opportunity to increase gig hours in times of crises such as the 2020 pandemic. Our results highlight the need to carefully balance the value of workers' legal protections against the loss in welfare that would result from a reduction in workhour flexibility.

Our estimates of reservation wages allow us to see how driver welfare is linked to the political support for flexible gig work. In the context of Proposition 22, a California ballot initiative that allowed app-based transportation and delivery companies to classify their drivers as independent contractors, we have three findings. First, drivers' earnings are positively associated with political support of Prop 22. Second, political ideology and engagement are powerful forces that can easily swamp positive worker welfare effects such as the earnings guarantee included in Prop 22. Third, in many of our models, we find that California counties with particularly low driver reservation wages were more skeptical about Prop 22. One conjecture is that voters do not read lower reservation wages as an indication of increased driver surplus. Rather, they see it as an (undesirable) dearth of economic opportunity.

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**Table 1 Descriptive Statistics**

<b>Shift-Level Statistics</b>					
Variable	Obs	Mean	Std. Dev.	Min	Max
engaged time (hours)	26,657,521	1.45	1.2	.19	7.14
shift pay	26,928,697	29.58	26.65	2	155.77

<b>Weekly Statistics</b>					
Variable	Obs	Mean	Std. Dev.	Min	Max
engaged time (hours per week)	4,207,615	9.11	8.97	.31	40.48
shifts per week	4,207,615	6.35	6.08	1	32
days worked	4,207,615	3.36	2	1	7
weekly pay	4,207,615	187.51	195.4	5.85	907.01
hourly wage (engaged time)	4,207,615	20.33	6.56	8.96	48.23

Note: Engaged time at shift and week levels, weekly pay, and hourly wage trimmed to 1-99% of distribution. Shift pay trimmed to 0-99% of distribution.

**Table 2a** Descriptive Statistics for the COVID-19 Period

<b>Pre-COVID-19 (March through June 2019)</b>	Obs	Mean	Std. Dev.	Min	Max
engaged time (hours per week)	910,220	8.55	8.6	.31	40.48
weekly pay	910,220	149.85	160.65	5.85	907.01
shifts per week	910,220	6.19	6.18	1	32
days worked	910,220	3.23	1.96	1	7
wage (weekly mean, engaged time)	910,220	17.29	4.95	8.96	48.23
<b>COVID-19 (March through June 2020)</b>					
engaged time (hours per week)	1,334,328	10.45	9.61	.31	40.48
weekly pay	1,334,328	241.84	223.06	5.85	907.01
shifts per week	1,334,328	7	6.35	1	32
days worked	1,334,328	3.62	2.04	1	7
wage (weekly mean, engaged time)	1,334,328	23.65	6.7	8.96	48.23

**Table 2b**            **Effect of COVID-19**

	(1)	(2)	(3)
	Engaged Time	Days Worked	Weekly Earnings
8/2019 to 2/2020	0.314***	-0.191***	-7.077***
[compared to 3/2019 to 6/2019]	(0.0158)	(0.00344)	(0.330)
3/2020 to 6/2020	2.369***	0.258***	39.48***
[compared to 3/2019 to 6/2019]	(0.0188)	(0.00631)	(0.605)
Polynomial time trend	yes	yes	yes
Constant	7.998***	3.179***	144.7***
	(0.0190)	(0.00217)	(0.208)
Observations	4,207,578	4,207,578	4,207,578
R-squared	0.011	0.010	0.040

Standard errors in parentheses

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

**Table 3 Regressions of Labor Supply on Hourly Wage**

	(a) OLS	(b) OLS	(c) IV – First Stage	(d) IV – 2SLS
hourly wage (engaged time)	-0.4244*** (0.1081)	-0.4689*** (0.1245)		6.0395*** (0.0209)
peak pay indicator			4.2133*** (0.0093)	
Constant	106.8936*** (2.5429)	107.9765*** (2.9308)	22.1477*** (0.0052)	
Observations	13,503,340	13,454,652	13,454,652	13,454,652
R-squared	0.2656	0.3592	0.1960	
Individual Fixed Effects	Yes	Yes	Yes	Yes
Block Time Fixed Effects	Yes	Yes	Yes	Yes
Individual X Block Fixed Effects	No	Yes	Yes	Yes
F-statistic for Weak Identification			180496	

Note: Each regression uses minutes of labor supplied (engaged time) while logged into the app as the outcome variable. Robust standard errors in parentheses.

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

**Table 4 Changes in Surplus from Gentle Scheduling, as Fraction of Weekly Earnings**

**Panel A: Switching Hours from Most Preferred to Less-Preferred Block**

To Less-Preferred Block:	Number of Drivers in Calculation	Mean	10 <sup>th</sup> Percentile	25 <sup>th</sup> Percentile	Median	75 <sup>th</sup> Percentile
<b>Weekday Blocks</b>						
Tue-Fri Lunch	6,478	-0.0516	-0.153	-0.0662	-0.0194	0
Mon-Thurs Before Dinner	22,125	-0.0436	-0.129	-0.0520	-0.0133	0
Mon-Thurs Dinner	41,099	-0.0542	-0.152	-0.0673	-0.0242	-0.00506
Mon-Thurs After Dinner	41,295	-0.0548	-0.155	-0.0686	-0.0243	-0.00416
Mon-Thurs “Late-Night”	44,133	-0.0686	-0.181	-0.0887	-0.0375	-0.0128
<b>Weekend Blocks</b>						
Sat-Mon Breakfast	10,351	-0.0906	-0.233	-0.128	-0.0570	-0.0212
Sat-Mon Lunch	6,207	-0.0546	-0.157	-0.0709	-0.0225	0
Fri-Sun Before Dinner	24,085	-0.0413	-0.124	-0.0489	-0.00999	0
Fri-Sun Dinner	42,831	-0.0482	-0.138	-0.0591	-0.0189	0
Fri-Sun After Dinner	45,268	-0.0517	-0.145	-0.0670	-0.0226	0
Fri-Sun “Late-Night”	46,128	-0.0702	-0.181	-0.0947	-0.0412	-0.0123
All Remaining Hours	39,047	-0.0950	-0.238	-0.131	-0.0614	-0.0254
Overall	51,231	-0.0608	-0.169	-0.0796	-0.0292	-0.00528

**Panel B: Switching Hours from Top 2 Preferred Blocks to a Longer Shift**

To Shift:	Number of Drivers in Calculation	Mean	25 <sup>th</sup> Percentile	Median	75 <sup>th</sup> Percentile
Dinner Every Day 5-9pm	44,167	-0.0693	-0.0906	-0.0316	-0.00327
Brunch Sat, Sun, Mon 7am-2pm	13,433	-0.0971	-0.134	-0.0543	-0.0135
Nights Fri, Sat, Sun 9pm-3am	45,359	-0.102	-0.138	-0.0646	-0.0239

Note: The calculations represent, for each block, the weekly change in surplus for each driver if he had to drive the same number of engaged hours he drove in the preferred block(s). The change for each driver is expressed as a fraction of his average earnings per week. Due to outliers caused by extremely elastic labor supplies for certain drivers, these statistics are calculated over the 5<sup>th</sup>-95<sup>th</sup> distribution in terms of the weekly change in surplus. Breakfast is 7-10am. Lunch is 10am-2pm. Before-dinner is 2pm-5pm. Dinner is 5pm-9pm. After-dinner is 9pm-12am. Late-night is 12am-3am – this is actually early morning of the next day but is more naturally thought of as late-night. The “all remaining hours” block covers 3am-7am each day, plus weekdays 7am-10am.

**Table 5 Changes in Surplus from Heavy-Handed Scheduling, as Fraction of Weekly Earnings**

Driver must work all hours in:	Change in Surplus, Mean Driver	Change in Surplus, Median Driver	Standard Deviation
Most-Preferred Block	0.438	0.271	0.492
Most Frequently-Driven Block	0.0479	0.0368	0.162
Least Frequently-Driven Block	-0.369	-0.240	0.538
Least-Preferred Block	-0.574	-0.380	0.602
N	45,796 drivers		

Note: The calculations represent the weekly change in surplus for each driver to drive, in a certain block, the same number of engaged hours he drove in all of his other blocks. The change for each driver is expressed as a fraction of his average earnings per week. Due to the presence of extreme outliers caused by extremely elastic labor supplies for certain drivers, these statistics are calculated over the 5<sup>th</sup>-95<sup>th</sup> distribution in terms of the weekly change in surplus.

**Table 6 Total Levels and Changes of Surplus for Various Scenarios, as Fraction of Weekly Earnings**

	Level of Surplus, Mean Driver	Level Standard Deviation	Change in Surplus, Mean Driver	Change in Surplus, Median Driver	Number of Drivers that Drop-out
Current Model with Full Flexibility	0.404	0.224	--	--	--
<b>Alternative Scenarios</b>					
A) Need to Commit Week Before	0.110	0.168	-0.293	-0.270	3,378
B) Need to Commit Day Before	0.126	0.196	-0.278	-0.253	2,771
C) Strict Assignment to Preferred Block	0.267	0.222	-0.137	-0.0868	6,403
D) Strict Assignment to Most-Frequently Driven Block	0.183	0.201	-0.220	-0.175	20,613
E) Strict Assignment to Least-Frequently Driven Block	0.0272	0.143	-0.376	-0.356	49,300
F) Strict Assignment to Least-Preferred Block	0.0223	0.107	-0.381	-0.361	53,601
N	63,497 drivers				

Note: The first two columns describe how much surplus would be generated for the sample of drivers per week under different scenarios using the estimates of mean reservation wage. The median level of surplus for the current model with full flexibility is 0.377. The second two columns describe the change in surplus that results when moving drivers away from the current model with full flexibility. For scenarios D, E, F, and G, drivers are required to work all hours during the block, and cannot pick up shifts in other hours. The final column provides a count of the number of drivers for whom the scenario has an expected negative surplus (and thus, who will choose not to work at all). For scenarios B and C, drop-outs are those whose expected labor supply is less than 10 minutes on average per week -- our definition of a committed driver.

**Table 7 Changes in Surplus by Number of Hours Driven per Week, as Fraction of Weekly Earnings**

	Number of Drivers	A) Need to Commit Week Before	D) Strict Assignment to Most-Frequently Driven Block	E) Strict Assignment to Least-Frequently Driven Block
0-5 Hours	13,013	-0.319	-0.294	-0.373
5-10 Hours	21,719	-0.299	-0.226	-0.372
10-15 Hours	13,052	-0.291	-0.196	-0.379
15-20 Hours	7,179	-0.277	-0.172	-0.375
20-25 Hours	4,042	-0.269	-0.167	-0.380
25-30 Hours	2,089	-0.252	-0.165	-0.382
30+ Hours	2,403	-0.233	-0.194	-0.413
Overall	63,497	-0.293	-0.220	-0.376

Note: The calculations represent, for the mean driver in each strata of average engaged hours driven per week, the change in surplus when moving from the current model to alternative scenarios A, D, and E. All calculations use the reservation-wage-based estimates. The sample includes all committed drivers in CA.



**Table 8 Earnings Guarantee**

	Obs	Mean	Std. Dev.	Min	Max
<b>1<sup>st</sup> Decile</b>					
wage (weekly mean, engaged time)	420762	11.79	1.47	8.96	13.66
earnings floor (\$, as per Prop 22)	420762	124.44	148.76	7.79	928.06
extra income Prop 22 (total, \$)	420762	52.51	68.22	1.94	891.71
<b>2<sup>nd</sup> Decile</b>					
wage (weekly mean, engaged time)	420761	14.59	.49	13.66	15.39
earnings floor (\$, as per Prop 22)	420761	161.99	165.52	6.99	928.06
extra income Prop 22 (total, \$)	420761	46.63	48.54	1.14	357.87
<b>3<sup>rd</sup> Decile</b>					
wage (weekly mean, engaged time)	420762	16.05	.37	15.39	16.68
earnings floor (\$, as per Prop 22)	420762	179.8	174.58	6.49	928.06
extra income Prop 22 (total, \$)	420762	40.2	40.35	.64	303.83
<b>4<sup>th</sup> Decile</b>					
wage (weekly mean, engaged time)	420762	17.28	.35	16.68	17.88
earnings floor (\$, as per Prop 22)	420762	191.95	182.08	6.09	928.06
extra income Prop 22 (total, \$)	420762	32.34	32.65	0	248.92
<b>5<sup>th</sup> Decile</b>					
wage (weekly mean, engaged time)	420761	18.49	.36	17.88	19.12
earnings floor (\$, as per Prop 22)	420761	200.05	188.08	5.74	928.06
extra income Prop 22 (total, \$)	420761	22.74	24.42	0	203.1
<b>6<sup>th</sup> Decile</b>					
wage (weekly mean, engaged time)	420761	19.76	.4	19.12	20.47
earnings floor (\$, as per Prop 22)	420761	199.84	194.65	5.73	928.06
extra income Prop 22 (total, \$)	420761	11.45	15.79	0	150.79

**Table 9 Descriptive Statistics for County-Level Variables**

	Mean	Std. Dev.	Min	Max
Number of committed drivers in county	34,786	53,923	502	271,018
<i>Aggregated statistics</i>				
Expected level of surplus from flexible model	161.4	27.83	117.8	243.3
Change in surplus over committing week before	105.7	16.09	81.24	153.6
Mean reservation wage when working	31.99	2.360	28.66	37.88
Mean reservation wage when not working	39.70	2.804	35.43	47.24
Change in mean reservation wage when working, compared to least-preferred scenario F	-17.03	2.160	-25.65	-14.78
Change in mean reservation wage when not working, compared to least-preferred scenario F	2.475	0.224	2.144	3.296
Average hourly wage (engaged time)	23.74	6.338	20.14	56.25
Extra weekly income from Prop 22 earnings guarantee	19.33	5.207	9.495	32.75
<i>County-wide statistics</i>				
Share in favor of Prop 22 (pp)	58.91	8.161	40.49	70.34
Share of eligible voters registered Republican (pp)	27.42	10.15	6.706	49.79
Prop 22 voter turnout (pp)	57.11	8.767	38.66	75.67
Population density (thousands of people per sq. mi)	1.079	3.076	0.0247	18.81
Number of restaurants (hundreds)	12.45	16.63	1.140	67.39
Population white non-Hispanic (pp)	45.59	18.40	10	84.70
Median household income (thousands of dollars)	79.39	22.65	48.47	138.5
<i>N</i>	38			

Note: County-level voting results for Prop 22 come from Politico. Share of eligible voters registered Republican (as of October 2020) and Prop 22 voter turnout rate come from reports released by the California Secretary of State. Population density was calculated using average population from 2010-2019, as per the Annual County and Resident Population Estimates dataset for California. The number of restaurants in a county is an average of Q1 and Q2 establishment counts using NAICS code 7225 from the Quarterly Census of Employment and Wages. Percent of population that is white non-Hispanic and median household income come from the 2019 American Community Survey.

**Table 10 Associations of Driver Surplus & Wages (levels) with County Support (pp) for Prop 22**

	(1)	(2)	(3)	(4)	(5)	(6)
	Using Expected Surplus of Fully Flexible Model		Using Mean Reservation Wage when Working		Using Mean Reservation Wage when Not Working	
Surplus from DoorDash	-0.1485*** (0.0490)	-0.0377*** (0.0133)				
Reservation wage			-2.3835*** (0.6565)	-0.3592 (0.2137)	-1.8122*** (0.4949)	-0.3192* (0.1639)
Average hourly wage (engaged time)	0.1052 (0.1537)	0.0886* (0.0486)	0.1470 (0.1652)	0.0908* (0.0501)	0.1404 (0.1658)	0.0949* (0.0498)
Population density (thousands per sq. mi)	-0.5678** (0.2181)	-0.1238 (0.0827)	-0.2082 (0.2848)	-0.0828 (0.0821)	-0.5403** (0.2369)	-0.1234 (0.0810)
Number of restaurants (hundreds)	0.0802 (0.0846)	0.0342 (0.0294)	0.0091 (0.0734)	0.0158 (0.0277)	0.0206 (0.0764)	0.0163 (0.0275)
Population white non-Hispanic (pp)	0.0068 (0.0738)	-0.2375*** (0.0665)	0.0438 (0.0686)	-0.2429*** (0.0708)	0.0427 (0.0730)	-0.2449*** (0.0710)
Median household income (thousands of dollars)	-0.0483 (0.0722)	0.0100 (0.0237)	-0.0190 (0.0681)	0.0006 (0.0281)	-0.0148 (0.0699)	0.0032 (0.0267)
Share of voters registered Republican (pp)		0.8119*** (0.0400)		0.8027*** (0.0346)		0.8042*** (0.0393)
Prop 22 voter turnout (pp)		0.3021** (0.1277)		0.3222** (0.1313)		0.3309** (0.1303)
Constant	83.5249*** (6.0308)	33.1219*** (5.9300)	131.2895*** (16.9209)	38.7516*** (8.3183)	127.0745*** (15.7655)	39.2251*** (8.4214)
Observations	38	38	38	38	38	38
R-squared	0.4115	0.9640	0.5244	0.9608	0.4881	0.9619

Note: Each regression uses the share of the vote in favor of Proposition 22 (percentage points) as the outcome variable. The surplus calculations are based off the sample of committed drivers, aggregated to the county in which they primarily drive.

Robust standard errors in parentheses.

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

**Table 11 Associations of Value of Flexibility & Extra Income (changes) with County Support (pp) for Prop 22**

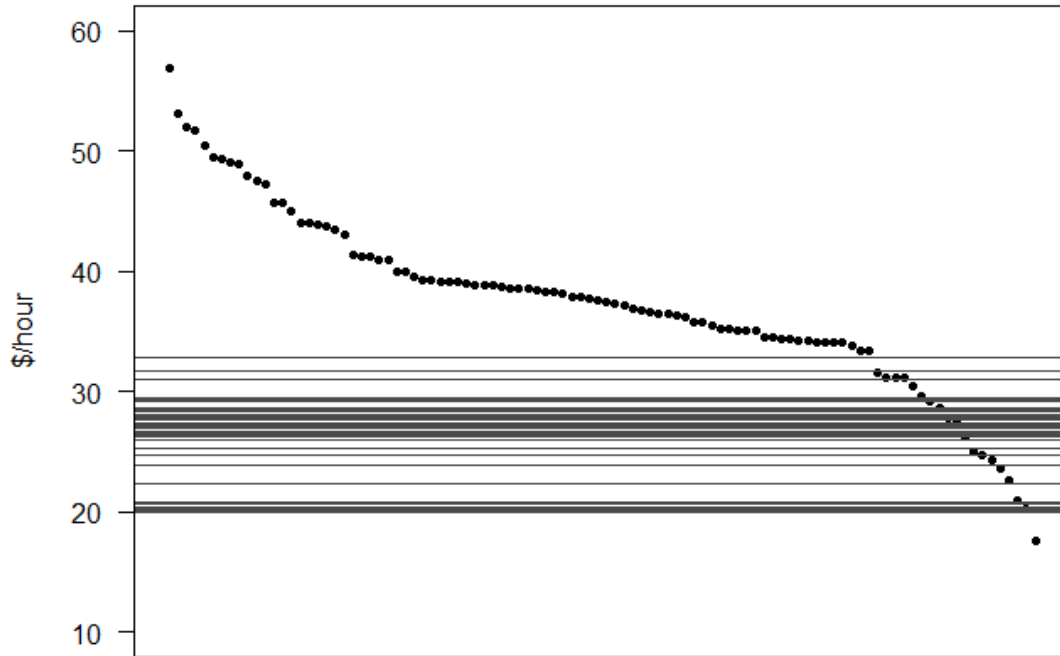
	(1)	(2)	(3)	(4)	(5)	(6)
	Using Changes in Surplus from Committing Week Before		Using Changes in Mean Reservation Wage when Working		Using Changes in Mean Reservation Wage when not Working	
Change in surplus from having flexibility	-0.1915*** (0.0485)	-0.0493*** (0.0177)				
Change in reservation wage			1.3473** (0.6446)	0.5968*** (0.1790)	-7.3775 (4.8673)	-3.4083* (1.6735)
Extra weekly income from Prop 22 earnings guarantee	0.9679*** (0.2633)	0.0164 (0.0849)	1.0149*** (0.3020)	0.0176 (0.0736)	0.9653*** (0.2963)	-0.0262 (0.0861)
Population density (thousands per sq. mi)	-0.5410*** (0.1799)	-0.2054*** (0.0701)	-0.9942*** (0.2941)	-0.4017*** (0.0840)	-0.7812*** (0.2241)	-0.2783*** (0.0934)
Number of restaurants (hundreds)	-0.0331 (0.0796)	0.0491** (0.0225)	-0.0445 (0.0894)	0.0539** (0.0206)	-0.0450 (0.0968)	0.0516** (0.0240)
Population white non-Hispanic (pp)	0.1308* (0.0676)	-0.2149*** (0.0724)	0.1240 (0.0764)	-0.2187*** (0.0664)	0.1493* (0.0800)	-0.2460*** (0.0706)
Median household income (thousands of dollars)	-0.0587 (0.0540)	0.0092 (0.0179)	0.0025 (0.0759)	0.0478** (0.0213)	-0.0713 (0.0522)	0.0049 (0.0139)
Share of voters registered Republican (pp)		0.8082*** (0.0582)		0.8232*** (0.0479)		0.8363*** (0.0596)
Prop 22 voter turnout (pp)		0.2381* (0.1191)		0.2263* (0.1160)		0.3103*** (0.1054)
Constant	60.1278*** (10.0481)	36.7245*** (5.4304)	58.0144*** (12.3495)	39.1759*** (5.5438)	58.7697*** (16.5932)	37.6804*** (7.3037)
Observations	38	38	38	38	38	38
R-squared	0.5753	0.9608	0.5145	0.9644	0.4886	0.9614

Note: Each regression uses the share of the vote in favor of Proposition 22 (in percentage points) as the outcome variable. The surplus and extra income calculations are based off of the sample of committed drivers, aggregated to the county in which they primarily drive. The changes in mean reservation wages are calculated by subtracting the mean reservation wages that result from strict assignment to the driver's least-preferred block from the mean reservation wages in the current arrangement. This result is robust to the same exercise using the driver's least-frequently-driven and most-preferred blocks.

Robust standard errors in parentheses.

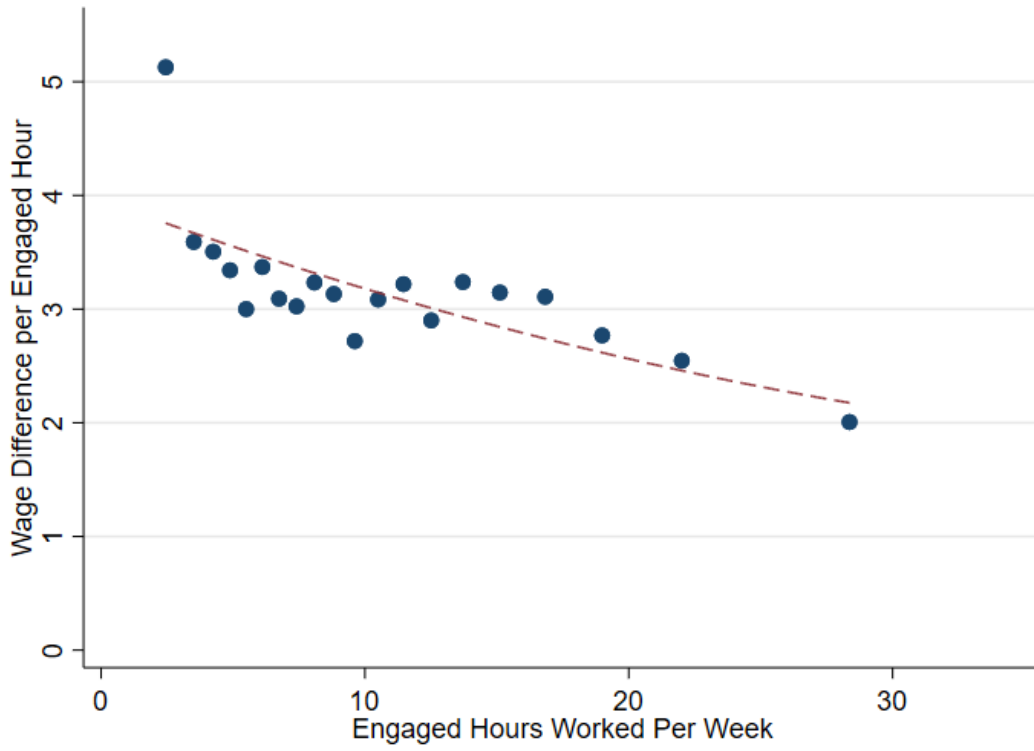
\*\*\* p<0.01, \*\* p<0.05, \* p<0.1

Figure 1 Reservation Wages for a Sample of 100 San Francisco Drivers, Tuesday Dinner Block



Note: The dots display the mean reservation wages for the weekday dinner block (5-9pm) for 100 randomly-selected drivers. The 52 horizontal lines show the expected wage in San Francisco for each week of the data.

Figure 2 Wage Boost per Hour from the Earnings Guarantee, by Engaged Hours Worked per Week



Note: The dots display the mean hourly wage boost with the earnings guarantee in place for different levels of engaged hours worked per week. Each dot represents 5% of the distribution of the sample of 65,597 committed drivers in California.