

# The Value of Flexible Work: Evidence from Uber Drivers

---

M. Keith Chen

*University of California, Los Angeles*

Judith A. Chevalier

*Yale University*

Peter E. Rossi

*University of California, Los Angeles*

Emily Oehlsen

*Uber Technologies*

Technology has facilitated new, nontraditional work arrangements, including the ride-sharing company Uber. Uber drivers provide rides anytime they choose. Using data on hourly earnings and driving, we document driver utilization of this real-time flexibility. We propose that the value of flexibility can be measured as deriving from time variation in the drivers' reservation wage. Measuring time variation in drivers' reservation wages allows us to estimate the surplus and labor supply implications of Uber relative to alternative, less-flexible work arrangements. Despite other drawbacks to the Uber arrangement, we estimate that Uber drivers earn more than twice the surplus they would in less-flexible arrangements.

The authors would like to thank Jonathan Hall, Elisa Long, Sylvia Hristakeva, and A. Ronald Gallant for valuable input. Peter Cohen, Dan Yavorsky, and Tianhao Wu provided invaluable technical and research assistance throughout this project. Through Emily Oehlsen, Uber Technologies provided the data used in this paper. Under the agreement granted the authors,

Electronically published October 31, 2019

[*Journal of Political Economy*, 2019, vol. 127, no. 6]

© 2019 by The University of Chicago. All rights reserved. 0022-3808/2019/12706-0004\$10.00

## I. Introduction

In recent years, a number of firms have launched business models that match demand for services to independent contractors providing those services. These businesses rely on independent contractors working intermittent or nonstandard hours. While these businesses typically do not offer many of the benefits of traditional employment relationships, they do provide an opportunity for service providers to earn compensation on a flexible schedule. Understanding the costs and benefits of such arrangements is of growing importance; recent survey evidence finds that 8.4 percent of US workers participate in independent contractor work as their primary job, a 22 percent increase over the last decade.<sup>1</sup> A much larger fraction, 30 percent, as estimated by Oyer (2016), participate in independent work as a primary or secondary activity.

The fastest growing part of this contract labor environment is digital platforms that instantaneously match buyers and sellers.<sup>2</sup> In this paper, we use data from nearly 200,000 drivers on Uber (a popular ride-sharing platform) to examine the benefits to drivers from labor supply flexibility and the costs (if any) from nonstandard hours. An important and unusual characteristic of ride sharing is that drivers can supply labor (or not) to the platform whenever they choose. Our goal in this paper is to measure the surplus to drivers (if any) that derives specifically from this flexibility.

We develop an approach in which we identify the taste for flexibility as being driven by (and equated with) time variation in a worker's reservation wage. If a worker had a constant reservation wage in all hours, the worker would be indifferent between a job that prescribed which specific hours the worker worked and a job that let the worker choose his or her hours. Time variation in a worker's reservation wage can result from stable differences in the mean reservation wage across time periods, for example, a preference to not work late nights. Time variation can also derive from transitory shocks to reservation wages. For example, a parent may have a very high reservation wage on a day that a child is home sick. Using data from drivers' decisions of whether and when to supply labor on the Uber

---

Uber has the right to review the paper "solely to confirm that confidential information is being represented in a non-misleading fashion" but not to dispute or influence the findings or conclusions of the paper. Chevalier and Rossi have no material financial relationships with entities related to this research. At the time of writing, Oehlsen was an employee of Uber Technologies. Chen is a former employee of Uber and, as a result, continues to hold stock options that may constitute a material financial position. Program files are provided as supplementary material online

<sup>1</sup> See Katz and Krueger (2016). Katz and Krueger define alternative work arrangements as "temporary help agency workers, on-call workers, contract workers, and independent contractors or freelancers." They find that the incidence of these types of work arrangements rose from 10.1 percent in February 2005 to 15.8 percent in late 2015.

<sup>2</sup> For example, Farrell and Greig (2016a) show that participation in platform work increased 10-fold between October 2012 and September 2015.

platform, we estimate each driver's pattern of mean reservation wages for different time blocks and also estimate the variance of each driver's reservation wages due to shocks. This allows us to estimate driver surplus from driving for Uber and to estimate the changes to that surplus that would result from requiring the driver to instead work specific patterns of hours. While the labor economics literature has addressed the importance of flexible work schedules, we are not aware of other research that evaluates the benefits derived from the ability to adapt the work schedule to reservation wage shocks.

Uber is a platform on which drivers, once approved, can use their own or rented cars to offer rides whenever they choose. There are no minimum-hours requirements and only modest constraints on maximum hours. As ride requests arrive, the Uber platform allocates these requests to nearby drivers. When a trip is completed, during the time of our data, riders pay a base fare plus a per-mile and per-minute rate. Fares are set at the city level and dynamically adjust (have "surge") when demand is high relative to the supply of drivers in a small local area. Both drivers and riders would see the surge multiplier, if any, before the trip commences and both the rider fare and the driver earnings increase proportionally during surge periods. Setting aside taxes, fees, and promotions, drivers earn a proportion of this payment less Uber's service fee.<sup>3</sup> Thus, the driver's compensation is a result of the driver's labor supply and location decisions as well as the demand and supply of other riders and drivers.

Because drivers can work whenever they choose, the compensation that a driver earns in a given hour is effectively determined by the willingness to work of the marginal driver. There is no cap placed on the number of drivers working in a manner that would support the wage. Thus, an important disadvantage of Uber, that wages are uncertain and compensation may be quite low, is a consequence of a central advantage of Uber, that drivers can work whenever they want. In our analysis, we focus on this aspect of the contractual arrangement between Uber and drivers—the fact that drivers can choose their own hours and can do so in real time. In order to investigate the relative value of flexible work arrangements to Uber drivers, we construct and estimate a simple empirical model of each individual driver's labor supply. In our model, a driver's expected schedule is determined by the weekly pattern of expected payouts from driving and the weekly pattern of her reservation wage; deviations from that schedule are caused by either shocks to the driver's reservation wage or shocks to her expected payouts.

<sup>3</sup> Occasionally, the Uber platform changes both how drivers and riders are matched and how fares are calculated. The description provided here, however, accurately describes the Uber platform throughout our data period. Uber's service fee varies across cities and has changed over time but was typically in the 20 to 30 percent range during our data period.

Our identification strategy, loosely speaking, is simple: if we see a driver supplying labor in an hour when the expected wage is \$15/hour and choosing not to supply labor in an hour when the expected wage is \$25/hour, controlling for a variety of other factors, we can infer that the driver's reservation wage is time varying. Furthermore, under various assumptions, we can make inferences about the driver's willingness to pay (if any) to avoid a counterfactual employment relationship that would require the driver to work during her high reservation wage hours or would prevent the driver from working during her low reservation wage hours. We can also make inferences about driver distaste (if any) for nonstandard hours. Finally, we can analyze patterns of driver behavior that are prevalent in the data and provide preliminary evidence about the types of flexibility sought by these labor suppliers.

In this paper, we use our time-varying reservation wage construct to examine Uber drivers specifically, but this approach may be useful in any environment in which workers face a portfolio of wage and hours choices. In particular, our setup is very helpful to examine choices by workers who have a primary economic activity or job and are making decisions about secondary work activities. Historically, a fairly small 5 percent of US workers hold multiple jobs at any given point in time; correspondingly, there is a relatively small economics literature on secondary job holders (see Paxson and Sicherman 1996; Renna and Oaxaca 2006). However, the proliferation of contingent workforce arrangements has increased the set of workers whose economic activity does not resemble working a single job as an employee for a single employer. The time-varying reservation wage model that we use in our estimation strategy can be used to examine workers' decisions about the portfolio of labor supplied.

Our paper proceeds as follows. Section II briefly reviews the literature on labor supply, job flexibility, and nonstandard hours. Section III describes our data sources and construction of the analysis data set. Section IV provides a first look at the habits of Uber drivers and suggestive evidence about their taste for flexibility. Section V introduces our labor supply model and outlines how we conduct inferences for that model. Expected labor surplus, labor supply elasticity estimates, and expected labor supply are discussed in Section VI. In Section VII, we examine the sensitivity of our model to exogeneity assumptions, alternative formulations of wage expectations, the presence of a rival ride-sharing service, and various aspects of our estimation procedure. Section VIII provides a conclusion and summary of our findings.

## II. Literature

For many jobs, work hours are fixed by the employer. This may be due to complementarities among employees, the shape of the hours/productivity

function, and/or fixed costs in staffing and monitoring workers. If jobs are at least partially inflexible, this suggests that workers will often find that both the total *quantity* of hours worked and the temporal *pattern* of hours worked mismatch their preferences. The hypothesis that the total quantity of hours is determined by the employer rather than as an individual negotiation between the employer and employee is supported by findings in Altonji and Paxson (1988), Senesky (2005), and Altonji and Usui (2007). In particular, there is evidence that many US workers would prefer to work fewer hours per week than required by the schedule set by their employer, if they could do so at their current hourly wages (see Rebitzer and Taylor 1995; Reynolds 2004). Consistent with this, the Council of Economic Advisors reports data from the National Study of Employers that suggest that 36 percent of firms with over 50 employees would allow some employees to transition from full-time to part-time work and back again while remaining in the same position or level, but that only 6 percent would allow it for most or all workers (see Council of Economic Advisors 2010).

The literature on the scheduling of hours is sparser than the literature on the total quantity of hours. Kostiuk (1990) documents that workers receive compensating differentials for evening shift work, while Hamermesh (1999) documents a secular decline in evening and weekend work from the early 1970s to the early 1990s. The pattern of observed changes is consistent with a model in which evening and weekend work is a disutility that higher productivity workers are willing to pay to avoid. This conclusion, that the reservation wage is on average higher in the evening and night due to disamenity effects, can be directly tested in our data.

More recently, a small literature has examined flexible workplace practices. For example, the Council of Economic Advisors (2010) reports that 81 percent of surveyed employers would allow some employees to periodically change starting and quitting times within some range of hours and 27 percent of employers would do so for most or all employees.<sup>4</sup> However, only 41 percent would allow some employees to change starting and quitting times on a daily basis and only 10 percent would do so for most or all employees. Thus, employers typically appear to have preferences for the particular hours of the day worked by employees. The reasons for this will vary across industries and jobs, but include at least monitoring costs, complementarities among coworkers, and the need for workers to interface with customers in real time. Interestingly, survey data from Bond and Galinsky (2011) suggest that lower wage employees have less flexibility than higher wage employees. Indeed, lower wage workers, particularly in the retail and hospitality sectors, cannot choose their hours, and the hours chosen by their employers frequently change from week to week. Using data from

<sup>4</sup> Data from the National Study of Employers.

the General Social Survey, Golden (2015) estimates that about 10 percent of the workforce is assigned to irregular and on-call work shift times and another 7 percent work split or rotating shifts and that this irregular work is more concentrated among lower wage workers. Although some cities and states have passed laws limiting the practice, it is common practice in retail and hospitality environments for workers to have to call in a few hours before a shift to determine whether they are needed (see Gustafson 2016).

The paper that perhaps has the most overlap with our own is Mas and Pallais (2016). Mas and Pallais conduct a survey of job applicants to a call center. Mas and Pallais experimentally alter the labor supply arrangements offered potential job applicants with a view toward estimating the willingness to pay for aspects of flexibility. Mas and Pallais find a low average willingness to pay for flexibility, although they find a substantial right tail of individuals whose willingness to pay is larger. They also find that job applicants have a high disutility for jobs with substantial employer discretion in scheduling; they attribute this primarily to a large disutility for evening and weekend hours. They find that the average worker requires 14 percent more to work evenings and 19 percent more to work on the weekends.

The nature of traditional employment relationships poses challenges for researchers who might try to investigate worker willingness to pay for more flexibility using methods other than surveys. In particular, in examining labor data, one can infer that a worker's total compensation exceeds the worker's reservation value for the total hours worked. However, in conventional job settings, one cannot infer that the average hourly compensation exceeds the hourly reservation wage on an hour-by-hour basis. There may be hours in which the hourly wage paid to the worker is less than the worker's reservation wage, but the worker nonetheless works because the hour cannot be unbundled from other hours in which the participation constraint is slack. Furthermore, there may be hours in which the worker would be willing to work at the worker's usual wage, but these hours are not an available option from the employer.

Because of these challenges, platforms such as Uber represent new opportunities both for individuals supplying labor and for researchers. Most importantly, neither the quantity nor pattern of hours worked are fixed. While contract and freelance work have been more prevalent in the economy, the evidence on independent contractor arrangements in the low-wage sector suggests that Uber (and its main competitor Lyft) are among a limited number of opportunities for fully flexible semiskilled work.<sup>5</sup> Critically, they offer workers the opportunity both to stop working upon realizing positive shocks to their reservation wages (e.g., a child falls ill or another job offers the opportunity to work an overtime shift) and to

<sup>5</sup> See Katz and Krueger (2016), fig. 7.

start working upon realizing negative shocks (e.g., an unexpected expense arises or an expected work shift at another job is canceled). This ability is likely of great importance to lower wage workers: the Federal Reserve Board recently reported that 46 percent of US households would have difficulty covering an unexpected expense of \$400 (see Board of Governors of the Federal Reserve System 2016).

Substantial research suggests that multiple-job holding has historically been limited to about 5 percent of the workforce, although it is more prevalent for workers in certain occupations (e.g., Lale [2015] reports that multiple-job-holding rates for teachers are no less than 13 percent). While multiple-job-holding rates are low, a much larger number of workers transition in and out of multiple-job holding over the lifecycle (see Paxson and Sicherman 1996; Renna and Oaxaca 2006; Lale 2015). Lale (2015) estimates that about 1 percent of full-time single-job holders and 2 percent of part-time single-job holders transition into multiple-job holding each month. In many ways, the Uber workforce dynamics resemble multiple-job-holding dynamics. Hall and Krueger (2016) examine survey evidence and Uber administrative data. They document that drivers cite flexibility as a reason for working for Uber and that many drivers report that Uber is a part-time activity secondary to more traditional employment. Their findings are consistent with the third-party survey in Campbell (2018). Campbell (2018) finds that only about one-third of ride-share drivers report that the majority of their income derives from driving. Prior to the introduction of these platforms, there were clearly fewer opportunities to undertake secondary work that could be accommodated around the schedule of the primary work. Using data from individual bank and credit card accounts, Farrell and Greig (2016a) present evidence that is strongly suggestive that workers supply more labor to online platforms such as Uber and Lyft when they receive negative shocks to their earnings in their other sources of employment.

Consistent with this, Hall and Krueger (2016) document that the hours supplied by drivers vary considerably from week to week. We examine drivers' labor supply in more detail. Because of the flexibility of the platform, a driver can decide whether to supply labor minute by minute, which in turn allows us to infer time patterns of the driver's reservation wage. If there are time periods in which there is on average a substantial disamenity value to driving, supply and demand should lead to an equilibrium of higher expected wages during the undesired hours. Both the typical weekly pattern and shocks to the driver's reservation wage can in principle be extracted. We examine each driver's labor supply decisions and estimate alternative scenarios that mimic the effects of traditional employment relationships.

While our focus is not on labor supply elasticities, this paper is also closely related to the literature that uses high-frequency data on labor

supply and wages to examine labor supply elasticities. In particular, Camerer et al. (1997) study the shift-ending decisions of New York City cabdrivers and find evidence for a negative labor supply elasticity. In contrast, Oettinger (1999) studies the decisions of individual stadium vendors to work or not work a particular game, and finds evidence of substantially positive labor supply elasticities. Farber (2005, 2015) reexamines New York City cabdriver data and finds that only a small fraction of drivers exhibit negative supply elasticities. Frechette, Lizzeri, and Salz (2016) also use data from New York City taxis to estimate a dynamic general equilibrium model of a taxi market. Drivers make both a daily entry decision and a stopping decision (in contrast to our setting, in which a driver could make multiple starting and stopping decisions). Stopping decisions are determined by comparing hourly earnings with the combination of a marginal cost of driving that is increasing in the length of a shift and a random terminal outside option.

As in our model, Frechette et al. treat individual drivers as competitive and, thus, keep track only of the aggregate state of the market (market-level hourly earnings) when making individual driving decisions. That is, the driver compares the opportunity cost and disutility of driving to the expected income. Important features of their model, as opposed to ours, are the incorporation of the constraints imposed by the medallion system (in particular the scarcity of medallions), regulations that make driving multiple short shifts unattractive, and regulations that effectively cap shift length. Because of these features, Frechette et al. model the mean value of the outside option as a fixed value depending only on the 8 hour shift and medallion type. The driver specificity derives from the independent and identically distributed (i.i.d.) error in the opportunity cost of driving and the i.i.d. error in the utility of starting a shift. Thus the mean and variances of the outside option are identified by the decision to leave a medallion unused for an entire shift and the decision to stop driving before the shift ends. Unlike the analysis we conduct for this paper, for Frechette et al. driver heterogeneity in the value of the outside option is not a primary focus.<sup>6</sup>

A feature of our sample of contractors raises a point that has perhaps been underemphasized in the literature. In all of these papers, calculations of supply elasticities and the value of flexibility are not undertaken on a random sample of workers or potential workers, and the estimates may not apply to other samples. For example, our study examines drivers on the Uber platform. While we have about 200,000 drivers in our sample, they are all individuals who selected into providing labor in this flexible

<sup>6</sup> There are other papers that use the New York City taxi data. However, both Lagos (2003) and Buchholz (2015) take the supply of taxis and drivers as exogenous and, thus, address economic questions distant from those that we consider.

work environment. They likely have a higher taste for flexibility, for example, than individuals who answered the employment advertisement used to create the sample in Mas and Pallais (2016). However, one reason the Uber driver sample is interesting is that technology platforms such as Uber and its closest competitor, Lyft, create opportunities for relatively low-skilled flexible work on a scale that does not appear to have been previously possible. Furthermore, given the substantial fraction of drivers who use the platform as a secondary economic activity, Uber provides a window on the preferences of those workers whose primary economic activity is such that the worker is willing to supply additional labor to a secondary one.

### III. Data Sources and Construction of Analysis Data Sets

Our data are provided by agreement with Uber. We start with the universe of all Uber driver hours in the United States from September 2015 to April 2016. We focus on the UberX platform, which is Uber's peer-to-peer service in the United States. We limit our study to UberX both because it is the service with the majority of Uber trips and because other Uber services have characteristics that complicate studying drivers' labor supply choices.

Data on Uber drivers are stored in two large tables: (1) a "trips" table that records both logins/logouts and trips made by the drivers, and (2) a "payouts" table that records the earnings and payments made to the drivers. Neither of these tables is in a form amenable to analysis with a labor supply model. Our first decision was to convert these data to an hour-by-hour record of driver activity and payments. Specifically, our data consist of an anonymized driver identifier and an hour-by-hour record of time spent active on the system, time driving, city, and payouts. For the purposes of standardizing analyses across cities, we convert all data to the driver's local time. This poses challenges in five Uber cities in which the greater metropolitan area spans a time zone border (and therefore in which drivers drive back and forth over the time zone border frequently); we omit these cities from our analysis.<sup>7</sup>

One issue in evaluating these data is that there is more than one way to define labor supply. Our view is that "working" means to be actively willing to supply labor. In the Uber world, this is done by turning the driver-side app on and agreeing to accept requests for rides. This is to be distinguished from a "browsing" mode in which the app is on but the driver has not indicated a willingness to accept rides. A driver is "active" in the Uber parlance if

<sup>7</sup> Uber markets that cross time zones are Yuma, Arizona; northwest Indiana; Louisville, Kentucky; Cincinnati, Ohio; and South Bend, Indiana.

he or she is en route to a passenger or carrying a passenger. Both the “working” state and the “active” state are alternative definitions of labor supply. In particular, the “working” state is likely to be an overestimate of labor supply, because some drivers make no effort to position themselves in a location likely to be productive. For example, a driver might have the app on to accept rides while working another job (say, landscaping), but realistically may not expect to get rides given the driver’s location. The “active” status is likely to be an underestimate of labor supply in that many drivers are actively attempting to get rides when they are not en route to a rider or driving one.<sup>8</sup> In our data construction below, we attempt to compromise between these definitions.

#### A. *Data Construction and Definitions*

For our analysis, we divide time into discrete hours as the unit of observation, 168 hours per week. We define a driver to be active in an hour if she is active for at least 10 minutes within that hour, and measure the driver’s discrete choice of being active in each of the 168 hour blocks.

We calculate the “wage” in an hour as a driver’s total earnings in that hour, divided by minutes worked, times 60. Our use of the broader measure of work in our calculation likely understates the effective wage. However, because differences in overall utilization and time spent waiting for a ride is a crucial difference in the profitability of different hours, we think it is important to use time working rather than time active in calculating wage metrics. However, by screening for a minimum level of 10 minutes active in the hour, we screen out drivers who have the app on but are not accepting trips, or who have the app on in remote locations where they may not be trying to find trips. There are a very small number of large payouts of more than \$250 (less than 0.001 percent) and we capped or winsorized these values at \$250.

On the Uber platform, drivers are expected to pay for both the capital costs of their vehicle and all costs of operating the vehicle. In our analysis, these costs are incorporated into the driver’s reservation wages. In part for this reason, our analysis of labor supply and surplus should be thought of as short run; drivers can be thought of as making a longer-run vehicle choice, then choosing labor supply conditional on that capital stock. Some differences in the equilibrium wages across hours may well be driven by common cost differences in driving those hours.

<sup>8</sup> An important feature of Uber, documented by Cramer and Krueger (2016), is that relative to taxi drivers, Uber drivers spend less of their travel time and less of their mileage with no passenger in the car. Nonetheless, time spent searching for passengers is nonzero and clearly part of the driver’s labor supply.

*B. Filters Applied to the Data*

Our full data set consists of 1,047,176 drivers who meet our 10 minute active threshold in 183,608,194 hours. Because we will be evaluating patterns of activities over time, we create a sample of drivers who are active in at least 1 hour for at least 16 of the 36 weeks we have available in our data. We will refer to drivers who meet these criteria as “active drivers.” There are 260,605 drivers who are classified as “active.” These active drivers are responsible for 140,282,451 hours, or 76 percent of total hours. We removed holidays and holiday periods<sup>9</sup> as these are unusual periods of Uber demand that occur at irregular intervals and we did not wish to expend parameters on accommodating this shift in demand. We also found irregularities with 4 hours (9 p.m. through midnight on April 20, 2016) likely caused by database errors, and removed these from our data. After removing holidays and these 4 hours, we have 130,557,951 hours remaining, or roughly 70 percent of our original data.

In order to form estimates of the expected wages that drivers face and that we use to estimate labor supply, we computed average wages by city, week, day, and hour. The assumption we will use (to be relaxed in Sec. VII) is that drivers do not forecast their individual wages for a particular hour, but can forecast the average wage being earned in their city. In order to ensure enough observations to reliably compute these averages, for our model estimates, we restricted attention to the top 20 US cities by volume of labor supplied on the UberX platform. This means that in estimating our model, our final estimation data set has data on 197,517 drivers who supply 102,280,904 (or 55 percent) of the total hours observed in the original data pull.

Our final-analysis data set used to estimate our model consists of information by driver, week, day, and hour of labor supplied and includes expected wages for each of the 197,517 drivers. This data set has 881,826,744 hourly observations.<sup>10</sup> Expected wage is merged in from our table of expected wages on the basis of the modal city for the driver in that week. If there are periods of inactivity that last more than 1 week (i.e., a gap of a week or more), we impute an expected wage equal to the average of the wage for the first nonmissing modal city before the week in question and the wage for the first nonmissing modal city after the week in question.

An important issue arises from our data-filtering process. In order to have a long enough time series to undertake estimation, we are using

<sup>9</sup> Nineteen days were excluded: Labor Day, Halloween and the day after, Thanksgiving and the day after, the week of Christmas, New Year’s Eve and New Year’s Day, Martin Luther King Day, Presidents Day, Columbus Day, and Veterans Day.

<sup>10</sup> If we observe at least one active hour in the day, we fill in all of the nonactive hours for that driver for that day with a labor supply of 0.

drivers who remain active in the Uber platform for at least 16 weeks. However, our understanding is that many drivers try out driving for Uber but abandon the platform. Cook et al. (2018) find that 68 percent of Uber drivers who start driving for Uber have abandoned the platform after 6 months (though, because Uber drivers do not have to formally quit, it is possible that some are on an extended break). The platform was growing rapidly during the time of our data; drivers who tried out the platform and then left presumably had lower labor surplus than the drivers who remained on the platform. Our data requirements force us to oversample drivers who remain on the platform for a long time.<sup>11</sup>

Before turning to the estimation of our model, we present some model-free evidence on labor supply flexibility using the full sample of 260,605 active drivers.

#### IV. Model-Free Evidence on Labor Supply Flexibility

##### A. *Uber Driver Labor Supply Patterns*

Our research is motivated by the unusual characteristics of this market, particularly the enormous flexibility allowed to Uber drivers. As discussed above, most workers in the economy choose among employers who offer fixed wage-hour bundles. Unsurprisingly, the hours supplied by Uber drivers are not identical to the hours worked by workers in more conventional job settings, and they vary from week to week.

There is tremendous variation in driver behavior across drivers and within driver across time. Figure 1 shows the driving history of 100 randomly selected drivers for 2 adjacent weeks near the middle of our sample. The 2 weeks for a given driver are shown in the same color immediately adjacent to each other. The lines represent all times that the driver is active over the course of the week. The drivers are ordered by quintiles of their total driving hours per week averaged over the whole sample.

Clearly, there is heterogeneity across drivers in hours worked. Some drivers drive very little overall and individual driving shifts can be short. Driver habits have some similarity across the two adjacent weeks. The hour bands tend to overlap somewhat but not perfectly across the weeks.

<sup>11</sup> This raises the question of whether Uber turnover is unusual relative to turnover rates at other part-time work. The Bureau of Labor Statistics reports annual worker separation rates of 53.6 percent in retail trade and 74.5 percent in leisure and hospitality (though this rate is for all workers, not just new workers). Lale (2015) reports that of the multiple-job holders in any given month, roughly 30 percent return to single-job holding the following month. Another 1.6 percent transition to nonemployment. Farrell and Greig (2016b) find, in a study of Chase account holders who have obtained earnings from at least one online labor platform, that dropping out within a year is substantially more likely for participants who earn a lower share of their total income from the platform. Against this backdrop of similar kinds of economic activities, Uber driver attrition does not appear to be unusual.

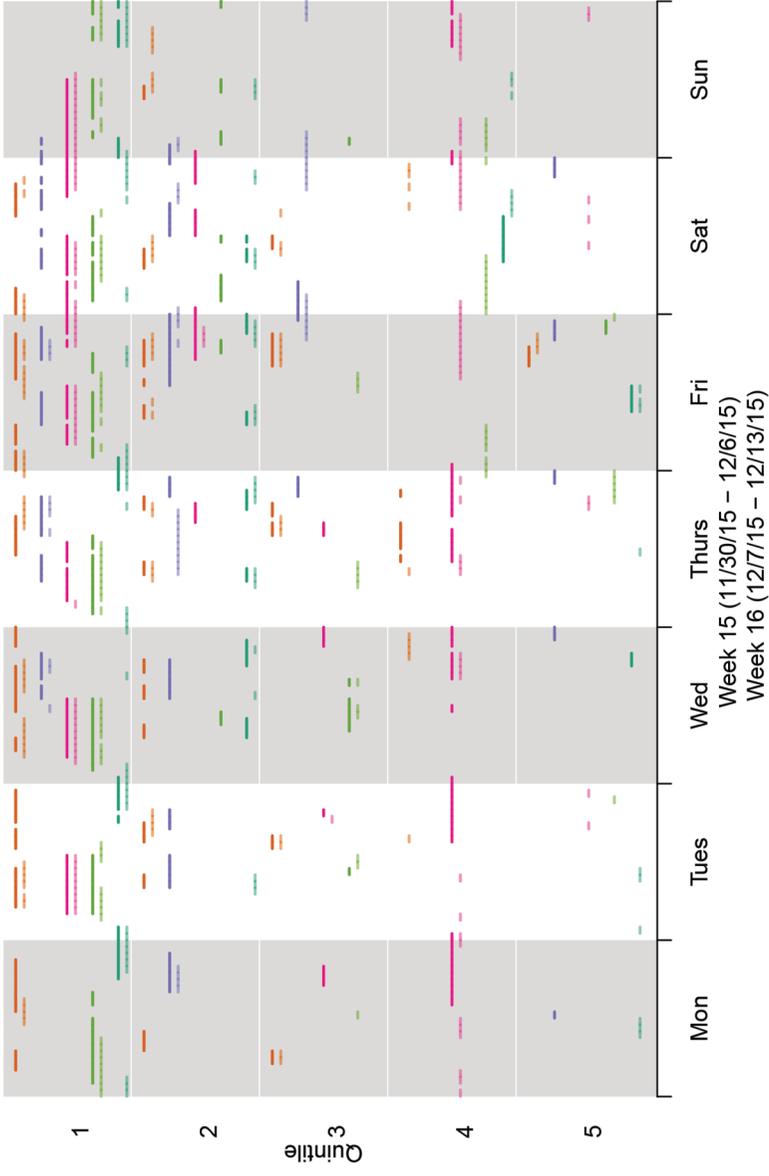


FIG. 1.—One hundred drivers' schedules for 2 weeks

The drivers who overall drive a lot (sorted near the top) do drive on average more than the drivers who overall drive less, but clearly this correlation is far from perfect, suggesting driver behavior is inconsistent over time. Thus, the figure suggests interesting variation across drivers in the total hours worked and in the particular choice of schedules worked. It also suggests that a given driver's behavior can look quite different over time. We explore these issues more thoroughly below.

Table 1 provides the distribution of total hours worked by week supplied by drivers in the full sample of "committed" drivers. Recall that we consider a driver active in any hour block when she was active for at least 10 minutes, and we count how many of the 168 hour blocks in the week the driver was active. The table displays the share of the drivers who were active on the system for various time bins. We use our base sample of drivers who are active at least 16 weeks during our 36 week study, but eliminate drivers before their first week of activity. Our summary results are similar to Hall and Krueger (2016).

Table 2 is the transition matrix of hours worked in contiguous weeks for drivers who meet our active driver criterion. This illustrates the extent to which a driver's total activity varies from week to week, an issue also studied by Hall and Krueger (2016) in their earlier sample. The stub column shows bins of hours of driver activity in a week, and the remaining columns show the share of the drivers who are active on the system for various time bins during the subsequent week. For example, of the drivers active from 21 to 30 hours in a week, 30 percent fall into the same time-supplied bin in the subsequent week.

Tables 1 and 2 reveal three interesting patterns. First, the overwhelming majority of Uber drivers are working part-time hours. Indeed, even among active drivers the majority of drivers work fewer than 12 hours per week. This is unsurprising given the survey evidence in Hall and Krueger (2016), which suggests that driving is complementary to other economic activities such as school attendance, caregiving, or employment. Second, a substantial fraction of drivers active in one week are simply not active

TABLE 1  
DISTRIBUTION OF ACTIVE HOURS  
FOR COMMITTED DRIVERS SAMPLE

Total Hours	Share of Driver Weeks (%)
0	19
1–4	11
5–12	21
13–20	17
21–30	14
31–40	9
41+	9

TABLE 2  
TRANSITION MATRIX OF HOURS WORKED IN CONTIGUOUS WEEKS

<i>t</i>	<i>t</i> + 1											
	0	1-4	5-8	9-12	13-16	17-20	21-30	31-36	37-40	41-45	46-50	>50
0	.49	.17	.11	.07	.05	.03	.04	.01	0	0	0	0
1-4	.28	.26	.18	.11	.07	.04	.04	.01	0	0	0	0
5-8	.18	.18	.21	.16	.10	.06	.07	.02	.01	0	0	0
9-12	.13	.12	.17	.18	.14	.09	.11	.03	.01	.01	0	.01
13-16	.10	.09	.12	.16	.16	.13	.17	.04	.02	.01	.01	.01
17-20	.08	.06	.09	.12	.14	.14	.23	.06	.02	.02	.01	.01
21-30	.06	.04	.06	.07	.10	.12	.30	.12	.05	.04	.02	.03
31-36	.05	.03	.03	.04	.05	.07	.27	.18	.09	.08	.05	.06
37-40	.05	.02	.03	.03	.04	.05	.21	.18	.12	.11	.08	.09
41-45	.05	.02	.03	.02	.03	.04	.16	.15	.12	.14	.11	.14
46-50	.05	.02	.02	.02	.02	.03	.12	.12	.10	.14	.13	.23
>50	.04	.01	.02	.02	.01	.02	.07	.06	.06	.09	.11	.47

the subsequent week; this is particularly true for drivers who had low activity the first week. Finally, while there is some tendency for drivers to work a similar number of total hours from week to week, there is substantial week-to-week variation in hours worked.

*B. Comparisons with Standard Work Schedules*

Given that Uber drivers are largely working part-time hours, it is not surprising that their pattern of hours worked does not necessarily resemble the pattern of hours worked by those with conventional jobs. Figure 2 compares the working habits of Uber drivers to the working habits of employed males over age 20 surveyed in the American Time Use Survey (ATUS) for 2014. The x-axis shows the 168 hours of the week beginning with Monday morning; the y-axis shows the ATUS and Uber data. The ATUS data document the fraction of the surveyed employed individuals who report working in a given hour of a given surveyed day. Thus, while most employed individuals in the ATUS report working at some point in the week, the ATUS data also include vacations, furloughs, and holidays. For this analysis, the universe of Uber drivers is our standard universe of committed Uber drivers who have logged at least one 10 minute session in the week. The graph reports the share of such drivers working in each of the 168 hours of the week (averaged over all of the weeks).

While the overall levels are difficult to compare, it is clear that work in the ATUS largely takes place between 9 a.m. and 5 p.m., whereas Uber drivers are more likely to be working at 6 or 7 p.m. than they are at 2 or 3 p.m. While male ATUS respondents are about half as likely to be working Saturday afternoon as in the afternoon on a weekday, Uber drivers are more likely to be working Saturday afternoon and evening than a

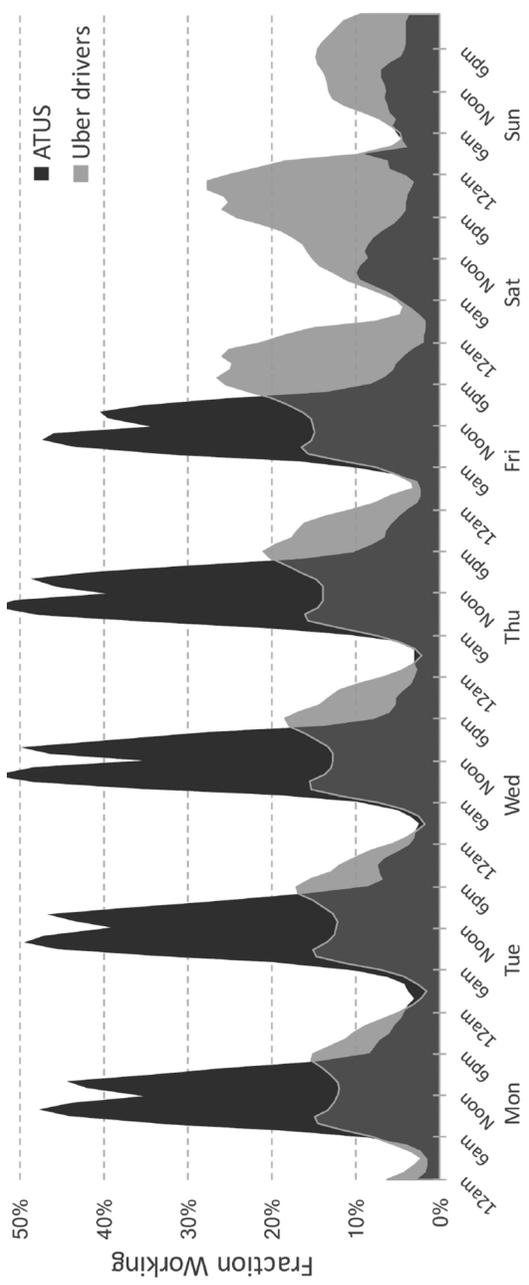


Fig. 2.—Comparison of Uber driver activity to workers in the ATUS

weekday afternoon or evening. Of course, this pattern of driving is the outcome of both supply and demand factors, and so we will incorporate payout information in our formal analysis in order to isolate labor supply factors.

We obtain further circumstantial evidence of the complementarity of Uber driving with more traditional work by examining work start and stop times in the ATUS versus Uber. Figure 3 again uses data for employed males over age 20 in the ATUS and shows the fraction who start working and stop working at a particular hour, averaged over all Wednesdays in 2014.<sup>12</sup> This is graphed against the hours of the day that Uber drivers begin and end driving sessions averaged across all Wednesdays in our data sample.<sup>13</sup> The figure expands on figure 2 and suggests that many Uber drivers begin driving during conventional work hours, but many also begin when conventional work hours end.

Given our definitions of starting and stopping, the majority of workers in the ATUS have only one start in a day; we find 114 starts in a day per 100 workers. However, Uber drivers are much more likely to drive in multiple sessions. We find 131 starts per 100 drivers who work within a day. In part this stems from the short sessions driven by many drivers; indeed, 20 percent of our starts are also stops, meaning that the driver starts and ends a driving session within a given clock hour. Of course, these behaviors are a function of both supply of drivers and demand for rides, so our more formal analysis will attempt to separate out supply and demand contributions for Uber driving.

### C. *Within-Driver Variation in Schedules*

We can express the extent to which drivers vary the particular hours worked from week to week as an average probability of repeatedly working an hour block across weeks. In our model section below, we will be contemplating the idea that drivers face a hierarchy of shocks to the reservation wage. Later in our formal model, we model a week shock (a shock to reservation wages that impact the whole week), a day shock that impacts a whole day, and an hour shock that idiosyncratically impacts a single hour. Here, we give an intuition of driver flexibility over time.

To do this, we divide the 168 hours of the week into 56 three-hour blocks ordered sequentially from the beginning of the week. We then ask the following: if a driver drives in a block in week  $t$ , what is the probability that the driver drives in that same block in week  $t + 1$ ? Then, to provide insight

<sup>12</sup> Stopping working is defined as ceasing reporting working in the ATUS without resuming working fewer than 2 hours later. Starting working is defined as working in an hour in which the worker did not work in either of the prior 2 hours.

<sup>13</sup> A driving session begins if the driver was not driving in the prior 2 hours but begins driving in an hour, and ends if a driver drives in an hour but not in the subsequent 2 hours.

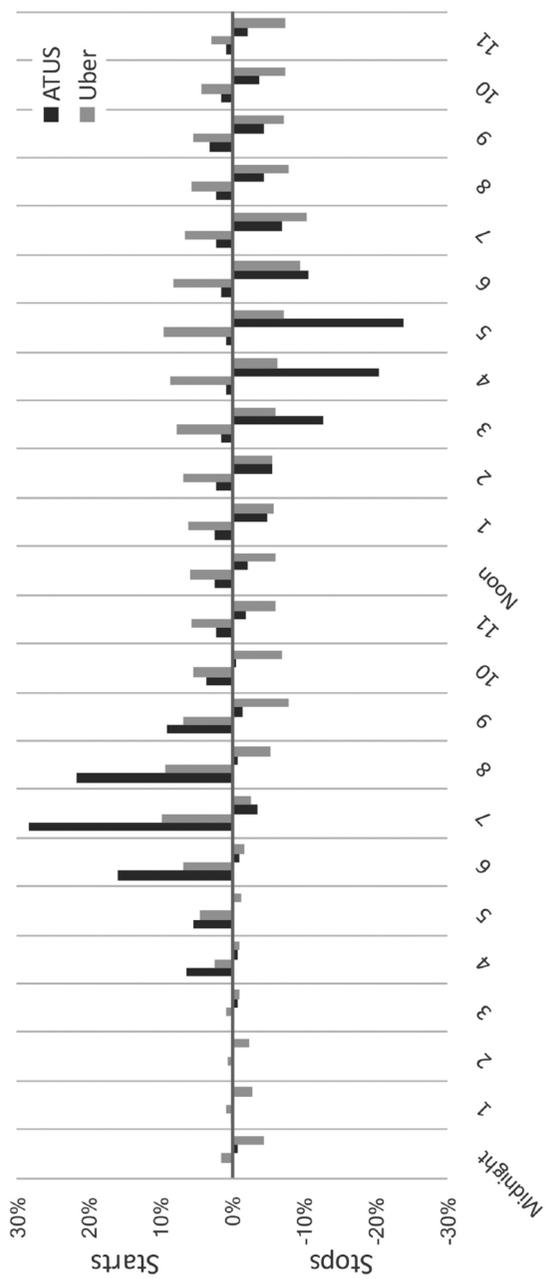


FIG. 3.—Comparison of Wednesday start and stop times on Uber versus the ATUS

into the ways that a driver can alter her schedule, we ask the same question, but condition on the driver working at some point in week  $t + 1$ . The idea is to identify the extent to which week-to-week variability is due to sitting out the entire week. Next, we trace working in the same block across weeks, but condition on driving sometime in the relevant day. The results are shown in table 3.

Table 3 shows that a driver who works in a particular block has a roughly 47 percent chance of working in that same block on the following week. If the driver did not work in a particular time block in week  $t$ , he or she has only a 9.3 percent chance of working in it the following week. The probability that a driver who worked in a block in week  $t$  will work in it again in week  $t + 1$  increases very little when excluding drivers who take the entire next week off. However, conditional on working sometime that day in the next week, the probability that a driver works in the same 3 hour block that he or she worked in the prior week rises to about two-thirds. This suggests that the particular hours driven by a given driver vary considerably, even conditioning on the driver working sometime in the day.

Of course, the pattern of driver hours is driven by both labor supply factors and labor demand factors. Driving patterns could be erratic in part due to drivers chasing erratic demand. We will evaluate this more formally below. However, we provide a summary graph, which is suggestive that supply factors, specifically time variation in drivers' reservation wages, are important for explaining the pattern of driving. Figure 4 graphs the share of drivers working in each of the 168 hours of the week (denoted "fraction working") against a measure of the payout of driving in the hour ("wage deviation," defined as percentage deviation from mean wage in that city week). The measure we use for realized payouts is the total payout per minute worked for drivers working in the hour block demeaned by the overall city mean (across all drivers and time periods), divided by the city mean. Thus, an hour with a value of 0 is an hour where a driver working would expect to earn the weekly mean payout of her city.

If labor supply was positive and constant across periods while demand varied across periods, one would expect either a zero or positive correlation between share working and the payout per minute worked. As demand and payouts increased, drivers would be expected to work more

TABLE 3  
CONDITIONAL PROBABILITIES OF WORKING A BLOCK IN CONSECUTIVE WEEKS

DID A DRIVER WORK A BLOCK IN WEEK $t$ ?	PERCENT WHO WORKED THAT BLOCK IN WEEK $t + 1$		
	Unconditional	Conditional on Working at All in Week $t + 1$	Conditional on Working That Day in Week $t + 1$
Yes	47.3	51.3	66.0
No	9.3	11.9	22.0

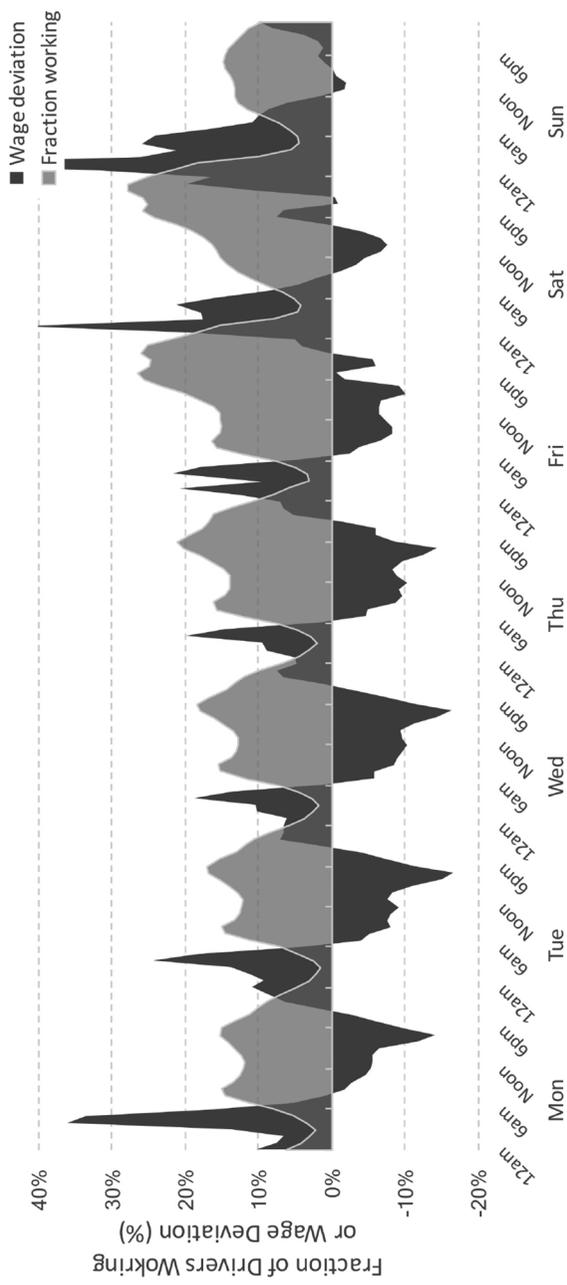


FIG. 4.—Correlation between when drivers work and when earnings are high

(perhaps to the point where payout per minute equilibrates across hours). However, there is an overall negative correlation between payout per minute and the share of drivers working; the overall correlation between the two series in figure 4 is  $-0.4$ . This suggests that there are some periods where payouts are high but where many drivers have on average higher reservation wages and choose not to drive.

Our model-free evidence of the volatility in driver hours presented above fundamentally does not allow us to disentangle two sources of week-to-week variation in hours worked for specific drivers. First, drivers have elastic labor supply and will be more likely to drive, *ceteris paribus*, when expected wages are higher. Second, drivers have volatility in their reservation wage. We pursue a model to allow us to disentangle these factors.

## V. A Model of Labor Supply and Inference Procedures

A simple model of labor supply specifies that drivers will supply labor if their reservation wages are less than the prevailing expected wage. That is, for a given period of time (which we take as 1 hour), we observe the labor supply decision,  $Y_{it}$ , as well as the expected prevailing wage,  $w_{it}$ , where  $Y_{it} = 1$  if driver  $i$  is observed to work in hour  $t$ , and 0 if not. We define “working” as having his or her driver app on and ready to receive requests from Uber riders as well as having at least 10 minutes of active time engaged in picking up a rider or on a trip. Expected wages are computed assuming drivers are rational and have access to the distribution of wages in a particular city and time. We estimate expected wages by computing the average wage over all Uber drivers in that city and time (see Sec. III above for details).

It should be noted that our measure of prevailing wages is not net of the variable costs of operating a vehicle. Therefore, our reservation wages should be interpreted as a gross quantity as well. Note that if a given driver has a car that is cheaper or more expensive to operate than the mean driver, this difference in expenses would be reflected in the driver’s mean reservation wage. Of course, the labor supply decision is based on the difference between prevailing and reservation wages, which does not depend on assumptions regarding the incorporation of operating costs.

### A. A Model of Labor Supply

We start by providing a simple intuition of our identification strategy. Consider a weekly 1 hour period, say, Tuesday, 2 to 3 p.m. For concreteness, assume that the mean prevailing wage for that hour is \$20 in a particular city, and consider a driver who works that hour most weeks. Our estimation would infer that the driver has a mean reservation wage for that hour that is less than \$20. Now, suppose that there are some slow weeks where

the prevailing wage is around \$15 for that hour. If the driver drives most of those weeks too, that suggests that the driver has a mean reservation wage for the hour that is less than \$15, and thus, on the more typical \$20 weeks, she is getting at least \$5 in surplus. In contrast, if the driver does drive the \$20 weeks usually but does not drive in the \$15 weeks, then our estimate of the mean reservation wage of the driver for that hour will be bounded between \$15 and \$20. This illustrates how the variation in the wage across weeks helps us to pinpoint the driver's reservation wage. With enough data, we would be able to see the wage at which the driver "drops out" from working in the hour. For the driver who usually drives the Tuesday 2 to 3 p.m. hour when the prevailing wage is \$20, if the driver does not drive that hour in some of the \$20 weeks, given her other behavior, her not driving will have to be ascribed to some kind of shock. The extent to which it is attributed to a shock to her hour, day, or week will largely be a function of whether the rest of her day or week are also outliers relative to her other behavior. The variance of the shocks experienced by the driver will be determined in part, loosely, by whether we sometimes observe the driver to not drive in that hour when it is more lucrative than a typical \$20 hour.

We now turn to a more specific description of our methods. The specification of the reservation wage process is crucial to determining the extent to which drivers are able to exercise flexibility in labor supply. As we have documented in Section IV, Uber drivers have both predictable and unpredictable patterns of labor supply. There is some predictability by day of week and time of day; for example, our results suggest that some drivers use Uber to supplement other jobs or responsibilities that occupy the standard 9 a.m. to 5 p.m. weekday period. Equally important, drivers change their work schedules from week to week, from day to day, and even from hour to hour. That is, there appears to be a good deal of evidence that, *ex post*, drivers behave as though they respond to events that are not constant from week to week. For these reasons, we postulate a model of reservation wages with both a predictable mean component as well as a random component that is unobserved by the econometrician but revealed to the drivers:

$$w_{it}^* = \mu_i(t) + \varepsilon_{it}. \quad (1)$$

Here  $w_{it}^*$  is the reservation wage of driver  $i$  in time  $t$ ,  $\mu_i(t)$  is the mean reservation wage at time  $t$ , and  $\varepsilon_{it}$  is a random shock to the reservation wage that will be resolved, for Uber drivers, before time  $t$ . That is, we assume that by at least the beginning of each time period (hour), each Uber driver has realized the shock and therefore simply compares his or her reservation wage for the hour to the expected wage to make a labor supply decision.

While the reservation wage  $w_{it}^*$  is unobservable to the econometrician, both driver labor supply,  $y_{it}$ , and the expected wage,  $w_{it}$ , are observed. Driver labor supply,  $y_{it}$ , takes the value of 1 in any hour in which the driver works

and zero in any hour in which the driver does not work. In an hour when the driver works, we can infer that the reservation wage is exceeded by the expected wage. Note that the expected wage in a given period can incorporate common knowledge by drivers about predictable events (such as concerts, conventions, and sporting events) that create peaks in demand for Uber services.

### 1. Mean Function

The mean portion of the reservation wage process drives the predictable portion of labor supply. For example, if a driver has a regular weekday job, the model can accommodate this with high reservation wages during the hours from 9:00 to 5:00 each weekday. Since these patterns of labor supply vary widely across drivers, we must provide mean function parameters that vary at the driver level. Even though we have a relatively large number of driver-hour observations, the censoring mechanism applied to the reservation process means that the information content of even thousands of observations is limited. We use a parsimonious specification by (1) grouping hours into blocks associated with a common shift in the mean reservation wage and (2) assuming driver preferences are stable and not allowing for trends or other time shifts. This implies that our mean function is a function only of the day and hour corresponding to time interval  $t$ ,  $\mu_i(t) = \mu_i(d, h)$ .

Our mean specification allows for nine parameters corresponding to the following blocks of hours:

1. MF\_am: Monday–Friday, 7 a.m.–12 noon.
2. MF\_afternoon: Monday–Friday, 1–4 p.m.
3. MF\_rush\_hour: Monday–Friday, 5–8 p.m.
4. MTh\_evening: Monday–Thursday, 9–11 p.m.
5. MTh\_late\_night: Monday–Thursday, 12–3 a.m.
6. FS\_evening: Friday–Saturday, 9–11 p.m.
7. FS\_late\_night: Friday–Saturday, 12–3 a.m.
8. MSu\_don:<sup>14</sup> Monday–Sunday, 4 a.m.–6 a.m.
9. Base: All remaining hours in the week.<sup>15</sup>

Below, we will consider robustness to estimating our model with more finely partitioned hour blocks.

<sup>14</sup> Dead of night.

<sup>15</sup> Note that each hour block extends from the first minute of the first hour in the block to the last minute of the second hour in the block specification; e.g., the MF\_am block extends from 7:00 a.m. until 12:59 p.m.

## 2. Error Components

We have observed that labor supply behavior of Uber drivers has an unpredictable component at the weekly, daily, and hourly frequencies. To accommodate these patterns of behavior, we employ a three-part variance components model for the shock to reservation wages:

$$\varepsilon_t = v_w + v_d + v_h. \quad (2)$$

In this model, each of the error components is i.i.d. normal<sup>16</sup> over its respective frequency with standard deviations  $\sigma_w$ ,  $\sigma_d$ , and  $\sigma_h$ , respectively. Here  $w$  denotes weekly,  $d$  denotes daily, and  $h$  denotes hourly. Thus, each time period (an hour) sees a new realization of the hour shock,  $v_h$ , each day a new day shock, and each week a new week shock.

Since each day within a week shares the common week shock and each hour within a day shares a common day shock, this creates the well known variance components covariance structure that can exhibit very high correlation between periods within each broader time frame. For example, hours within the same day have a correlation of

$$\rho_d = \frac{\sigma_w^2 + \sigma_d^2}{\sigma_w^2 + \sigma_d^2 + \sigma_h^2}.$$

These correlations are driven by the relative magnitudes of the error components. The error covariance matrix of the reservation wage shock in (2) is block diagonal across weeks, with hours within a week having a covariance structure given by

$$\Omega_w = (I_{\text{nd}} \otimes \Sigma_d) + \sigma_w^2 \iota_w \iota_w', \quad (3)$$

$$\Sigma_d = \sigma_h^2 I_{24} + \sigma_d^2 \iota_d \iota_d'. \quad (4)$$

Here “nd” is the number of days in a week and allows for weeks with less than 7 complete days,  $\iota_w$  is a vector of  $\text{nd} \times 24$  ones, and  $\iota_d$  is a vector of

<sup>16</sup> Normal error components imply that the reservation wage process is multivariate normal over the 168 hours that comprise 1 week. The assumption of normality allows us to specify a model in which the mean of reservation wages can be determined independently of the size or variability of the shocks or unpredictable component of reservation wages. One possible drawback to this assumption is that there is some probability that reservation wage realizations will be negative (this may be very small). Some might suggest modeling the log-reservation wages. While this certainly removes the possibility of negative reservation wages, this assumption creates other undesirable problems. If we assume log-normal reservation wages, then high mean reservation wages are also associated with high variances. This means that we cannot independently vary the degree to which drivers have unpredictable (large shock) patterns vs. when they work on average. To take the example of someone with a high reservation wage during the day (due to another work opportunity), the log-normal model would also require that he or she be more unpredictable during the day than on weekends and evenings. We do not want to impose this sort of restriction on driver behavior.

$d \times 24$  ones. While  $\Omega_w$  is high-dimensional, the patterns of covariance are generated by only three variance component parameters. Variance component models have been criticized on the grounds of inflexibility (all covariances are positive and the same within an error component block, e.g., within a day). In our case, the variance components are interpreted as shocks to reservation wages that come at various frequencies in the lives of Uber drivers. Each component has meaning due to its association with a dimension of labor supply predictability.

Flexibility is conceptualized as the ability to respond to different kinds of shocks. Benefits of flexibility will be related to the relative magnitudes of these shocks. While Uber drivers can respond to each kind of shock, this is not true for many other labor supply arrangements. For example, a standard 9–5 factory shift job does not offer flexibility from hour to hour or from day to day. Typically, workers have a fixed number of pre-arranged days off, and a very limited ability to work less than a full shift. On the other hand, some taxi-style jobs allow for substantial day-to-day flexibility. If a taxi driver enters into daily rental agreements with the taxi owner, and the driver receives a large positive daily shock to reservation wages, then the driver simply does not work in that day. However, to amortize the fixed fee of renting the taxi, the driver would typically work almost all hours of a particular shift. Thus, the taxi driver can respond to weekly and daily shocks but is more constrained in her ability to respond to hourly shocks. If Uber drivers experience very small hourly shocks but large daily shocks, the Uber system will not afford drivers much value in terms of captured surplus relative to traditional taxi-style arrangements.

### B. Likelihood

Our model is a latent normal<sup>17</sup> and correlated reservation process coupled with a censoring function that indicates whether or not the observed wage rate exceeds or is less than the reservation wage:

$$y_{it} = \begin{cases} 1 & w_{it}^* < w_{it}, \\ 0 & w_{it}^* \geq w_{it}, \end{cases} \quad (5)$$

$$w_{it}^* = \mu_i + \varepsilon_{it}, \quad (6)$$

$$\text{Var}(\varepsilon_{it}) = I_N \otimes \Omega_w. \quad (7)$$

<sup>17</sup> Mean reservation wages are apt to be large relative to the variance of the error components. We seldom find any negative reservation wages, even though this is theoretically possible with a normal distribution.

Here  $\Omega_w$  is given by (3) and  $N_i$  is the number of weeks we observe driver  $i$ .<sup>18</sup> Given a specification of the mean function, the likelihood function for this model can be written down by first observing that, conditional on the observed wage vector, each week is independent of every other week:

$$\ell(\mu, \sigma_w, \sigma_d, \sigma_h | y, w) = \prod_{\text{wk}=1}^{N_i} \ell_{\text{wk}}(\mu, \sigma_w, \sigma_d, \sigma_h | y_{\text{wk}}, w_{\text{wk}}).$$

The computational problems of evaluating this likelihood are associated with the likelihood for each week. We observe a vector of 168 indicator variables corresponding to each hour of the week.<sup>19</sup> These are censored versions of the vector of latent normal variables in which the censoring is dependent on the observed wages for each hour. The variance component structure results in a potentially highly correlated latent normal vector. This means that the probability of the observed vector of labor supply decisions must be computed as the integral over a specific region of a 168-variate normal distribution:

$$\ell_{\text{wk}} = \int_{A(y_1, w_1)} \int_{A(y_2, w_2)} \dots \int_{A(y_{168}, w_{168})} \phi(x | \mu, \Omega_w) dx_1 dx_2 \dots dx_{168}. \quad (8)$$

Here we have suppressed the notation for the  $i$ th driver and the regions are defined by

$$A(y, w) = \begin{cases} \{w^* : w^* \leq w\} & y = 1, \\ \{w^* : w^* > w\} & y = 0. \end{cases} \quad (9)$$

There are no reliable methods for calculating (with a reasonable degree of accuracy) such high-dimensional integrals of a multivariate normal over a cone. Instead, we will employ a data augmentation strategy in a hybrid Markov chain Monte Carlo (MCMC) method as outlined below.

### C. Identification

Our model is closely related to the multivariate probit model. In this model, there is a latent regression model for each time period. We only observe the sign of these latent variables,  $y_i^* = x_i' \beta + \varepsilon_i$ :

<sup>18</sup> We impose the constraint that we observe drivers for complete days only. We fill out the days with zeros for those hours we do not observe labor supply. Typically, Uber drivers enter and exit our sample of 38 weeks on days of the week that make for incomplete (less than 7 days) weeks. For these weeks, we use the same variance component model and  $\Omega_w$  is modified to include blocks corresponding only to the number of days in the incomplete week.

<sup>19</sup> Not all weeks in our data have all 7 days as we removed holidays and drivers start and leave their Uber arrangements, creating incomplete weeks. For these incomplete weeks, we use the appropriate number of hours,  $nd \times 24$ , and the  $\Omega$ -matrix is adjusted accordingly.

$$y_i = \begin{cases} 1 & y_i^* > 0, \\ 0 & y_i^* \leq 0. \end{cases} \quad (10)$$

Typically, the errors are assumed to have a multivariate normal distribution,  $\varepsilon \sim N(0, \Sigma)$ . This model is not identified as the equation for each time period can be scaled by a (possibly different) positive constant. Thus, in the standard multivariate probit model, only the correlations are identified, not the full variance-covariance matrix of the latent error terms. However, our model of labor supply has two additions: (1) the censoring point is no longer fixed at zero but varies from observation to observation to the extent that observed wages,  $w_{it}$ , vary across observations, and (2) our reservation wage model of labor supply imposes an exact coefficient restriction that achieves identification. We can write out the model in the form of a multivariate probit as follows:

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

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

Thus, we impose the restriction that the coefficient on wages in the latent variable model is equal to  $-1$ .

The extent to which the model parameters are well identified in our sample depends on the variation in expected wages as this determines the censoring point in the distribution of latent reservation wages. Ideally, we would like to have a great deal of wage variation as well as variation that covers a wide range of the support of the distribution of reservation wages.

The magnitude of expected wage variation across the week averaged across cities and time is illustrated in figure 4. However, this masks the variation across weeks and hours that a driver in a given city would experience. Figure 5 graphs expected wages for each hour of the week for each week in our sample period for Los Angeles. Each week is shown in a different color. Recall that expected wages average over the idiosyncratic experiences of different drivers.

For Los Angeles, modal wages for Uber drivers are centered around \$20/hour with a great deal of dispersion (note that this is after Uber fees but before automobile expenses). Notice that the pattern of expected wages is similar from week to week. It is also clear that weeks that are low-earning weeks for a given hour appear more likely to be lower-earning weeks overall. The patterns illustrated here for Los Angeles are typical for all of our cities. To explore the extent of variation in expected wages, we conduct an analysis of variance by factor, including city,

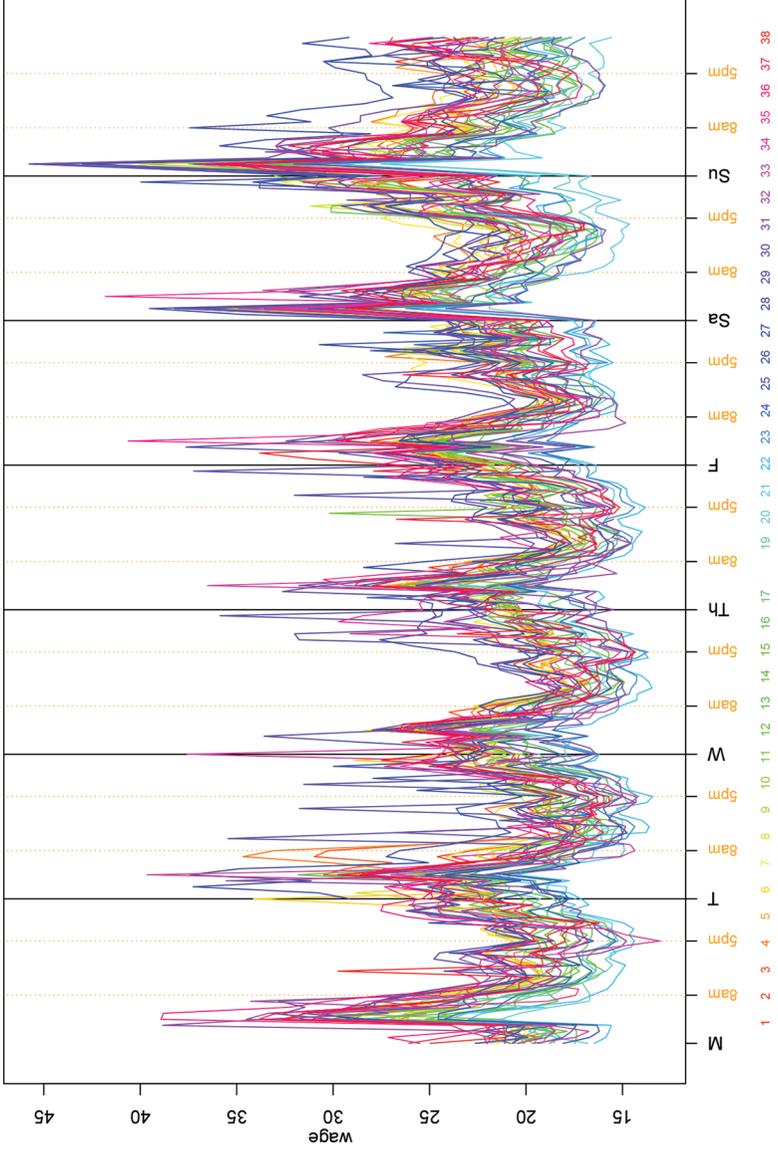


FIG. 5.—Variation in expected wages in Los Angeles

week, and day. That is, we regress expected wages on the appropriate set of dummies (for city and week in sample, and for the day of the week) and report the standard deviation of the residuals. Figure 6 shows bar plots of these residual variances for both expected wage and log expected wage. The leftmost bar shows the overall variance before regressing on dummy variables. The subsequent bars show the residual variance after introducing each incremental set of dummies. We see that even within city, week, and day of week, there is a great deal of variation with a standard deviation of over \$3 per hour which corresponds to variation in wages of at least 10 percent.

While our model is parametrically well identified, the question of nonparametric identification remains. We observe about 35 weeks of hourly data on most drivers, which means that we have something on the order of 5,000 observations per driver. We also have a very large cross section of drivers (about 197,000). Given that we are making inferences on the driver level, the cross-sectional sample size does not help with identification unless we impose some sort of further structure such as a particular random coefficient distribution. Nonparametric identification can only be achieved as the number of observations per driver tends to infinity as well as over a continuous distribution of realized wages (censoring points). Without some restrictions on the class of error shock distributions, we do not believe it is possible to establish fully nonparametric identification.

Details of our estimation method are given in the appendix (available online).

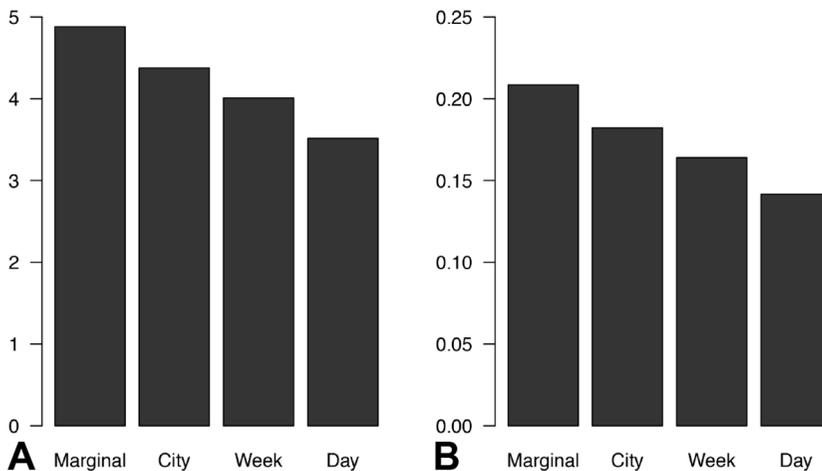


FIG. 6.—Variation in expected wages. *A*, Expected wage. *B*, Log expected wage.

*D. Model Results and Fit*

Our model estimates, for each driver, a mean reservation wage for each hour block, plus the variance components of week, day, and hour shocks. We first explore overall model fit. Figure 7 shows actual versus predicted labor supply by hour of the week. The black line connects the observed labor supply for each of the 168 hours of the week, averaged over all of our 197,000 drivers. The red line provides the expected labor supply by hour from our model fits. The vertical colored bands correspond to the hour blocking used for estimation of the mean wage. In spite of our rather dramatic simplification in which we blocked 168 hours each week into only nine groups, the model tracks the observed labor supply quite well.

Uber driver surplus can derive from a variety of factors. First, some drivers will have low reservation wages overall and will derive surplus from the difference between those reservation wages and the prevailing hourly wage. For an extreme case, consider the lonely driver who enjoys driving and talking to customers. This driver is clearly not the marginal driver who sets the wage, and this inframarginal driver clearly earns surplus. Second, some drivers will have reservation wages that are systematically heterogeneous across the hour blocks, and the Uber structure allows the driver to drive only in the lower reservation wage hours. For example, a driver who always works a valuable noon to 8 p.m. job can systematically not work in those hours. This driver earns surplus by avoiding work in those hours but working in other hours when the primary job is unavailable. Third, some drivers will have significant variance in their reservation wages that differ from week to week and the Uber arrangement allows the driver to shift driving hours. For example, an actor can choose not to drive whenever he is called for an audition. A retail worker can work when a shift has been canceled. Finally, a driver who has fairly uniform reservation wages across hours can earn surplus by “picking off” the high wage hours (such as the bar closing hours or when a concert or other event is taking place).

As expected, our results suggest that Uber drivers do not have homogeneous preferences for time of day and day of week. Figure 8 provides scatter plots of normalized mean reservation wage estimates. Recall that each driver has a separate and possibly unique mean reservation wage for all of the 9 hour blocks. For example, the *y*-axis of the left panel of figure 8 shows the mean reservation wage for the Monday–Friday rush hour block for a sample of drivers relative to the base period. The mean reservation wages range from a large positive to large negative deviation from the base period estimates, suggesting that preferences for the Monday–Friday rush hour block are very heterogeneous. In addition, there is a positive correlation between preferences for the Monday–Friday afternoon (horizontal axis) and Monday–Friday rush hour block as might be expected for two contiguous hour blocks. On the other hand, there is a clear negative correlation between preferences for the weekday afternoons versus late night

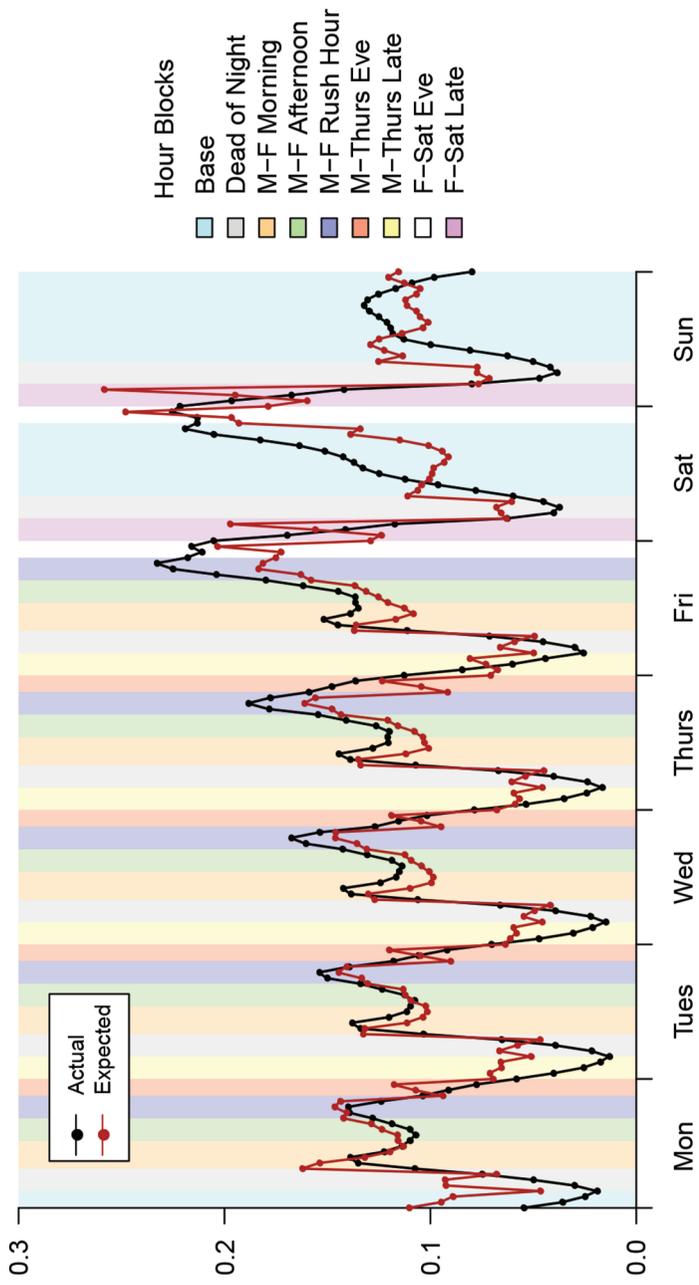


FIG. 7.—Expected versus actual labor supply by hour of week

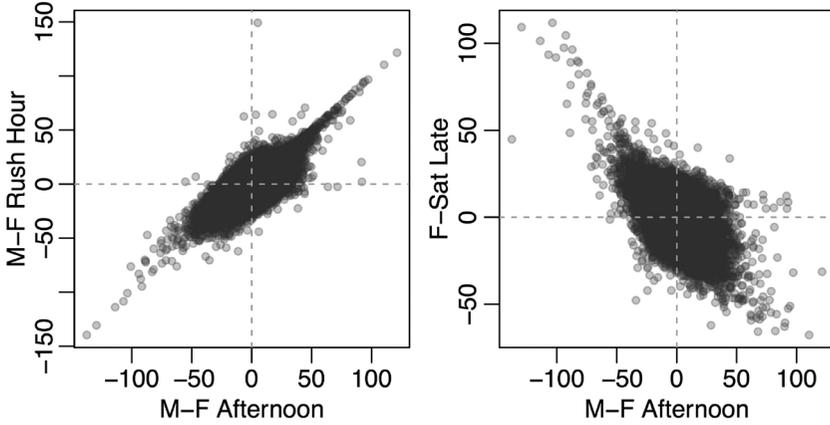


FIG. 8.—Scatter plots of mean reservation wage parameters

on Friday and Saturday (right panel). The ability to drive when these reservation wages are low is likely to be an important component of overall labor surplus.

Another important part of our estimation is the variance component estimates. Our MCMC procedure provides draws from each of the 197,000 driver posteriors in our estimation sample. We summarize these draws by computing the mean draw, which is a simulation-based estimate of the posterior mean. The posterior mean is often used as a Bayesian estimate. Figure 9 shows the distribution across drivers of the estimates of each of the

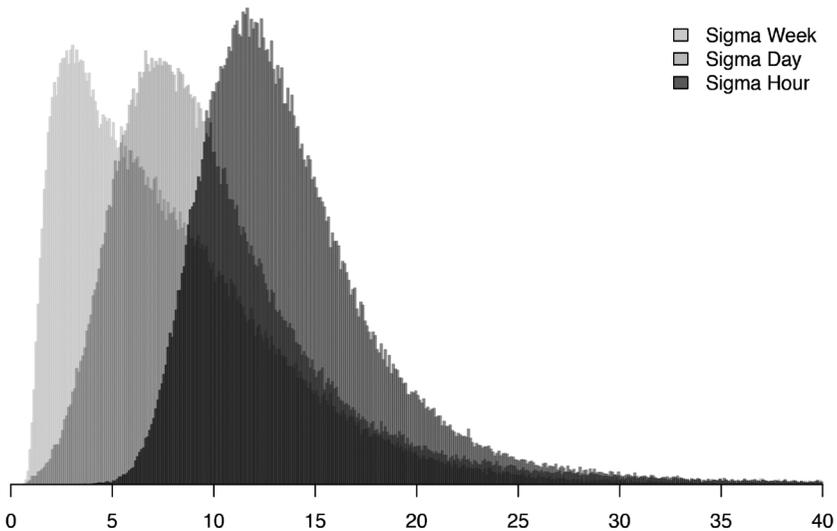


FIG. 9.—Variance component estimates

three variance components associated with week, day, and hour shocks ( $\sigma_w$ ,  $\sigma_d$ ,  $\sigma_h$ ). The sizes of the shocks are measured as standard deviations. We see that all shocks are large. The largest shocks are the hourly shocks; the median hourly shock standard deviation is \$12.94. Daily shocks are somewhat smaller with a median of \$9.02. Weekly shocks are the smallest but still appreciable with a median of \$6.76. Notice that the shock standard deviation estimates have a long right tail; some drivers experience very large shocks. Intuitively, large variances will be found for drivers whose hours driven vary a great deal from week to week and for whom driving time hardly demonstrates a discernible weekly pattern. The results suggest that the drivers in our sample experience large shifts in reservation wage that are not consistent from week to week and, thus, may place a large value on a flexible work arrangement. Adaptation to hourly changes in reservation wages will likely be an important component of overall labor surplus.

It may also be helpful to examine the distribution of reservation wages directly rather than simply examining shock standard deviations. Figure 10 shows the distribution of reservation wages for 100 drivers in Philadelphia for the Monday to Thursday evening hour block. The drivers are selected randomly from the set of drivers who otherwise meet our inclusion criterion, who drove in Philadelphia but no other city during our sample period, and who have driven in the Monday to Thursday evening hour block at least once during our sample period. The black dots show the estimate of

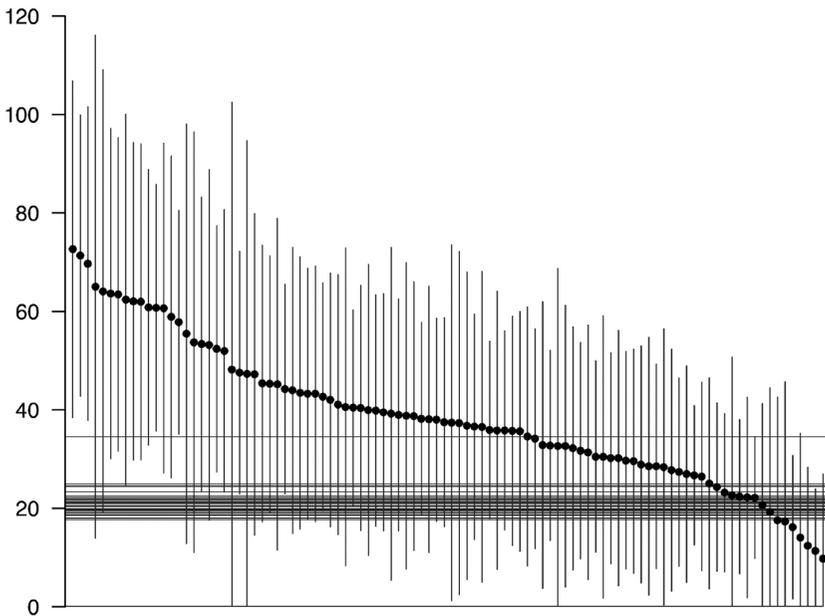


FIG. 10.—Detail for Thursday evening hour block for 100 Philadelphia drivers

the mean reservation wage for each driver for the hour block. The vertical gray bars show the 10th to 90th percentiles of the estimated distribution of the driver-specific reservation wage. The horizontal lines are the city mean wages for this hour block for each of the approximately 35 weeks in our sample. While most mean city wages hover around \$20, there is 1 week where the block has a very high effective wage.

Most of our individual driver estimates of the reservation vastly exceed the prevailing wage. This makes sense; in any given hour block, a small fraction of the drivers in our sample are driving. When we calculate hour-by-hour expected surplus, it will necessarily be truncated at zero because drivers will only drive if they achieve nonzero surplus. The substantial variance shows that upward and downward variation to the driver's typical reservation wage will be an important input to both the driving decision and the surplus calculation.

Our procedure also allows us to estimate labor supply elasticities for each driver as well as the aggregate elasticity of demand. The individual elasticities are calculated simply. Start with the median weekly wage profile faced by a given driver who drives in a given city. Our estimates suggest how many hours we would expect that driver to supply labor. Next, perturb the weekly wage profile for a single week and calculate, based on the individual driver's parameters, the change in hours supplied. This represents the driver-specific short-run wage elasticity. Figure 11 shows both the distribution of labor supply elasticities by driver as well as the relationship between labor supply elasticities and average hours worked

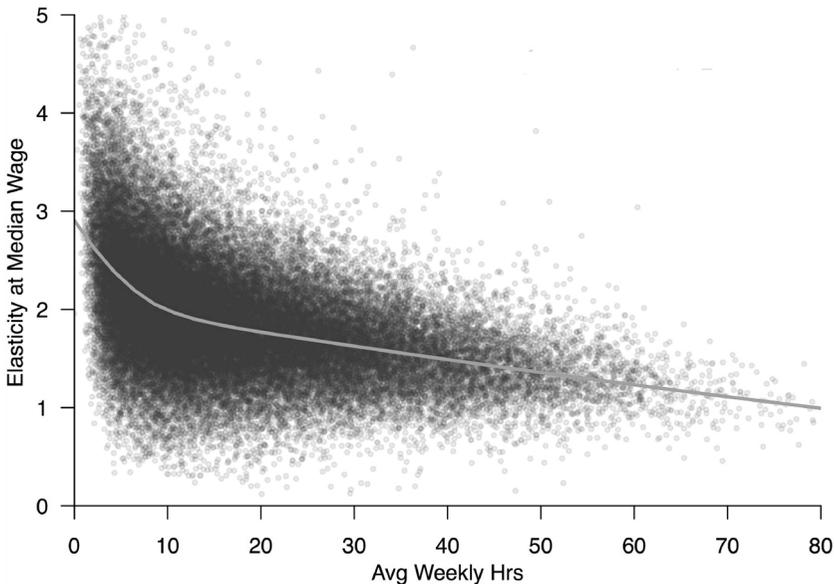


FIG. 11.—Labor supply elasticities

per week. The 25th percentile of driver labor supply elasticity is 1.81, the median 1.92, and the 75th percentile is 2.01.

Our labor supply elasticity estimates are very high by the norms of the labor literature, with the vast majority of drivers having labor supply estimates between 1 and 2. There are a few interesting things to note about this. First, as Oettinger (1999), Chetty (2012), Keane and Rogerson (2015), and others all note, there are a number of distinct reasons to be concerned that labor supply elasticities are typically underestimated in the micro literature. In particular, Chetty (2012) explores the potential role of optimization frictions and demonstrates that intensive margin elasticity estimates are very sensitive to even small optimization frictions. Adjusting for these frictions leads to larger estimates than those that have been reported in the literature. As our environment has effectively no frictions, it may not be surprising that we find higher labor supply elasticities than have been found in the literature.

As discussed in Section IV, the drivers vary greatly in the level of labor supply offered with the bulk supplying around 10 hours per week but with a considerable right tail. Drivers who drive a different number of mean hours have a differential ability to respond to wages. For example, a driver who drives only a few hours per week may choose to systematically “pick off” the highest wage hours, thus demonstrating substantial elasticity. Drivers who work 40 or more hours in the week cannot adjust their pattern of hours to pick off the highest wages. This is demonstrated in figure 11 as the scatter plot of elasticities on the vertical axis against average hours supplied per week. The plot shows a clear downward relationship between labor supply elasticity and average hours worked. The line on the plot is a non-parametric regression fit. Drivers who work only a handful of hours per week have much higher estimated elasticity than do drivers who work a conventional 40 hours per week. As much of the literature focuses on the labor supply elasticities of full-time workers, the elasticities for the higher labor supply drivers are perhaps most comparable to the literature.

## VI. Driver Surplus

We have postulated a flexible but parsimonious model of labor supply which allows for heterogeneity across drivers and features both predictable and unpredictable aspects of labor supply. It is also clear from our initial exploratory analysis that Uber drivers exercise ample flexibility in their labor supply both in the level or average number of hours per week as well as the pattern of hours and days on which labor is more frequently supplied. In addition, our fitted model of labor supply shows very large error components, implying that flexibility to adjust to random shocks could be an important component of value to Uber drivers. In this section, we compute measures of expected surplus from the Uber labor arrangement as well as alternative arrangements that afford less flexibility.

### A. *Surplus Measure*

Our goal is to compute the expected surplus for each driver. In our model, drivers will work only if their surplus (excess of wage over reservation wage) is positive. We will compute the expected surplus, which is the probability that the surplus is positive (i.e., the driver decides to work) times the expected surplus conditional on working. Consider hour  $t$  in which a driver faces wage  $w_t$ ; expected surplus can be written as

$$ES_{i,t} = (w_t - E[w_{i,t}^* | w_{i,t}^* < w_t]) \Pr[w_{i,t}^* < w_t]. \quad (11)$$

To produce a welfare measure for each driver, we sum expected surplus to the driver-week level and compute the average of this measure over all weeks for which we observe the driver in our data. This averages the measure over the distribution of prevailing wages faced by each driver. In the end, we will have one expected surplus value for each driver and we can gauge the impact of various flexibility restrictions on both the total Uber driver surplus as well as the distribution of this surplus across drivers.

### B. *Constraints on Flexibility*

We start with the base case, in which the Uber system imposes no constraints on labor supply flexibility. At the granularity of hour blocks, Uber drivers can choose to work at any time. Because they can make moment-to-moment decisions about labor supply, it is natural to assume that they make these decisions with full knowledge of both the mean reservation wage as well as the realization of shocks to their reservation wages. That is, if there are weeks, days, or hours where the cost of supplying labor is very high due to other time commitments, Uber drivers are free to choose not to work either for the whole week, specific days in the weeks, or even specific hours in the week. This flexibility means that a driver can make labor supply decisions based on the idiosyncrasies of her pattern of mean reservation wages as well as the shocks.

For example, if an Uber driver holds down a traditional 9–5 job, then we would expect that driver's mean reservation wages for work at Uber to be very high during the 9–5 weekday hours. In addition, the Uber system affords drivers flexibility with respect to unpredictable changes in time commitments. For example, while a driver might normally work a particular time block within the week, if a primary employer offers an overtime shift, the driver will not work. The ability to respond to deviations from the normal pattern of reservation wages could be a significant source of value for the Uber-style flexible work system, and we might expect that individuals with high variances in their hourly reservation wages will find the Uber platform very attractive.

Thus, our approach to welfare calculations is to compare the Uber system “base case” to alternative arrangements in which constraints are

imposed on the driver's labor supply flexibility. The Uber system allows each driver to make hour-by-hour labor supply decisions without any constraints. As such, the Uber system represents a base case with the highest degree of flexibility. We will compare the expected surplus under the most flexible Uber-style system with a host of other labor supply arrangements that differ in the nature and severity of constraints on labor supply flexibility.

**BASE.** Drivers can adapt to weekly, daily, and hourly shocks with full knowledge of the prevailing wages for that city, week, day, and hour and full knowledge of the realization of all of the shocks.

We will consider three basic types of constraints.

### 1. Lessened Adaptation to Driver Shocks

In the base case, drivers make labor supply decisions with full knowledge of the realized value of all weekly, daily, and hourly shocks. We consider two other scenarios of decreasing flexibility.

**CASE A.** *Cannot adapt to hourly shocks.*—In this scenario, we do not allow the driver to adapt to hourly shocks. One interpretation is that the driver must make a decision about which hours she will work at the beginning of each day with knowledge of the distribution of hourly shocks to the reservation wage but without knowledge of the realization of the shocks for each hour in that day. This case affords flexibility to adapt to weekly and daily shocks but not to hourly shocks.

**CASE B.** *Cannot adapt to daily and hourly shocks.*—Here, we do not allow the driver to adapt to daily or hourly shocks. The driver can adapt to changes in shocks from week to week but not within the week.

It should be emphasized that these scenarios are restrictions only on the driver's ability to adapt to shocks. We still allow the driver to respond to changes in the prevailing wage, and we assume that drivers have perfect foresight as to the prevailing wage. We also allow the driver to have a driver-specific profile of mean reservation wages that can vary by day of week and hour of day. That is, cases A and B are still much more flexible than most conventional work arrangements.

### 2. Commitment over Longer Time Horizons

In scenarios A and B above, the driver can vary labor supply from week to week in response to weekly shocks as well as predictable changes in prevailing wages. Our monthly scenario restricts this ability.

**MONTH.** *Month-long labor supply commitment.*—At the beginning of each month the driver must make a commitment to work the same schedule each week and cannot respond to weekly, daily, or hourly shocks. In addition, the driver cannot respond to changes in prevailing wages from week to week in the month. We assume that the driver must make decisions

based on average weekly profile of prevailing wages, where this is averaged over the month ahead. The driver can also take his or her mean reservation wage for each hour block into account.

### 3. Institutional Constraints

In many labor markets, workers face institutional constraints that require a form of precommitment to specified blocks of time.

*TAXI. Taxi constraints.*—In the taxi industry a driver must choose between one of each of three 8 hour shifts on a daily basis. If a taxi worker decides to work a shift, the driver is effectively obligated to work the entire shift by virtue of high lump sum rental prices for the taxi cab. Thus, the taxi labor system has flexibility from day to day and week to week but imposes block constraints on the hours within each day.

We model these taxi constraints simply. Drivers know their week and day shocks but cannot adapt to hourly shocks and must decide which if any of the three shifts to work based on the expected surplus for the entire shift.<sup>20</sup> In most taxi settings, the high up-front fee charged to taxi drivers effectively necessitates working the whole shift, and we examine that simplified model. While we mimic the taxi environment specifically, this institutional constraint is also informative about any conventional 8 hour shift working environment. Indeed, it is much more flexible than many work environments in that the worker has a day-by-day choice of which shift to work.

#### C. Calculating Expected Surplus

##### 1. Base Case

In the base case, the driver sees the realization of week, day, and hour shocks and is able to make a labor supply decision conditional on these shocks, mean reservation wages, and prevailing wages for that city, week, day, and hour. Thus, expected surplus for each hour can be computed from the expectation of the reservation wage conditional on working, which is the expectation of a truncated normal random variable. We sum these for each hour of the week and then average them over all complete weeks in the data (note that typically, there are incomplete weeks at the beginning and ending of the drivers' data records as drivers do not begin and end their affiliation with Uber on the first hour of each week, which we take to be midnight to 1 a.m. on Sunday).

<sup>20</sup> Indeed, our model of the taxi constraint still provides the driver more flexibility than he or she might have in a true taxi environment in which decisions to rent a cab for the shift are often bundled across days.

Consider week  $l$ ,

$$ES_{i,l} = \sum_{d=1}^7 \sum_{h=1}^{24} (w_{ldh} - E[w_{i,ldh}^* | w_{i,ldh}^* \leq w_{ldh}]) \Pr[w_{i,ldh}^* \leq w_{ldh}], \quad (12)$$

and the surplus for driver  $i$  is

$$ES_i = \frac{1}{N_i} \sum_{l=1}^{N_i} ES_{i,l}, \quad (13)$$

where  $N_i$  is the number of complete weeks observed for driver  $i$ .

The conditional expectation of reservation wage given the decision to work can easily be computed as it is the mean of the truncated normal random variable:

$$\begin{aligned} E[w_{i,ldh}^* | w_{i,ldh}^* \leq w_{ldh}] &= \mu_i(d, h) + E[\xi | \xi \leq w_{ldh} - \mu_i(d, h)] \\ &= \mu_i(d, h) - \sigma_\xi \frac{\phi(\text{TP}_{i,ldh} / \sigma_\xi)}{\Phi(\text{TP}_{i,ldh} / \sigma_\xi)}, \end{aligned} \quad (14)$$

where  $\text{TP}_{i,ldh} = w_{ldh} - \mu_i(d, h)$  is the truncation point and  $\xi \sim N(0, \sigma_w^2 + \sigma_d^2 + \sigma_h^2)$  is the sum of the shocks. The probability of working is simply given by the normal cumulative density function evaluated at the truncation point:

$$\Pr[w_{i,ldh}^* \leq w_{ldh}] = \Phi\left(\frac{\text{TP}_{i,ldh}}{\sigma_\xi}\right). \quad (15)$$

## 2. Cases A and B: Restricted Ability to Adapt to Shocks

In cases A and B, the drivers are limited in their ability to respond to shocks. In case A, they cannot adapt labor supply to the hourly shock, while in case B they cannot adapt to both the hourly and daily shocks. In these cases, the expected surplus can be computed in exactly the same manner except that we must refine the random variable  $\xi$ . In case A,  $\xi = v_w + v_d$ , while in case B,  $\xi = v_w$ . That is, drivers can only use the expected value<sup>21</sup> (0) of the shocks as they are assumed not to be able to respond to the realization.

## 3. Taxi Constraints

Here the driver can observe weekly and daily shocks but not hourly shocks and must choose one of three 8 hour shifts or not to work at

<sup>21</sup> Note that each of the variance components (shocks) are assumed independent so  $E[v_h | v_w, v_d] = E[v_h]$ .

all. This means that the driver must calculate the expected surplus for each shift. The driver chooses the shift with largest positive surplus. If no shifts have expected surplus that is positive, then the driver does not work at all. At the beginning of each day, the driver knows  $v_w + v_d$ , mean reservation wages for each hour of that day,  $\mu(d, h)$ , and prevailing wages for each hour of that day. To make the labor supply decision and compute expected surplus, we simply sum over all of the hours in each shift. The surplus for shift  $j$  is

$$\begin{aligned} S_j &= \sum_{t \in S_j} w_t - w_t^* \\ &= \sum_{t \in S_j} (w_t - \mu_t) - N_{S_j}(v_w + v_d) - \sum_{t \in S_j} v_{h,t}, \end{aligned} \quad (16)$$

where  $w_t^* = \mu_t + v_w + v_d + v_{h,t}$  and  $N_{S_j}$  is the number of hours in shift  $j$ . The expected surplus from the driver's point of view is given by

$$\begin{aligned} E[S_j | v_w, v_d] &= \delta_j - N_{S_j}(v_w + v_d) \\ &= \delta_j - \xi_j, \end{aligned}$$

where  $\delta_j = \sum_{t \in S_j} (w_t - \mu_t)$ . The driver will find the shift with the maximum value of  $\delta_j$  and will work that shift if

$$\begin{aligned} \max(\delta_j) - \xi_j &\geq 0, \\ \xi_j &\sim N(0, N_{S_j}^2(\sigma_w^2 + \sigma_d^2)). \end{aligned} \quad (17)$$

From the inequality above, we can compute both the probability of working on that day and the expected surplus from the shift worked (note that we assume that under the taxi arrangement drivers work only one shift). The probability of working is given by

$$\Pr[\text{work}] = \Pr[\max(\delta_j) - \xi_j \geq 0] = \Phi\left(\frac{\max(\delta_j)}{\sigma_\xi}\right).$$

Expected surplus given that the taxi driver decides to work is

$$\begin{aligned} E[S | \text{work}] &= \max(\delta_j) - E[\xi | \xi \leq \max(\delta_j)] \\ &= \max(\delta_j) + \sigma_\xi \frac{\phi(\max(\delta_j)/\sigma_\xi)}{\Phi(\max(\delta_j)/\sigma_\xi)}. \end{aligned}$$

Unconditional expected surplus is, therefore,

$$ES = \Phi\left(\frac{\max(\delta_j)}{\sigma_\xi}\right) \left[ \max(\delta_j) + \sigma_\xi \frac{\phi(\max(\delta_j)/\sigma_\xi)}{\Phi(\max(\delta_j)/\sigma_\xi)} \right]. \quad (18)$$

Note that  $\sigma_{\xi}$  is determined by the number of hours that are in shift  $j$ . In our taxi scenario, all shifts are 8 hours long. To compute total expected surplus for the taxi arrangement, we simply sum over all days (note that the wages will vary across days) and express this on a weekly basis.

4. Month-Long Time Commitment

In this case, the driver cannot respond to any shock and must commit to a work schedule for a month at time (note that for simplicity’s sake, we define a month as a 4 week interval). In addition, the driver cannot respond to week-to-week changes in prevailing wages and must make decisions based on the average prevailing wages for that month.

Let  $w_{mdh}$  be the average wage for each day of the week and hour of the day for a 4 week period  $m$ :

$$ES_{i,m} = 4 \sum_{d=1}^7 \sum_{h=1}^{24} [w_{mdh} - \mu_i(d, h)]^+ \tag{19}$$

Again, we simply average these measures over the number of 4 week periods observed for each driver to obtain  $ES_p$ .

D. *Expected Surplus and Labor Supply Computations*

For each of the drivers, we compute Bayes estimates of the mean reservation wage parameter and Bayes estimates of each of the variance components necessary for the expected surplus computations. Figure 12

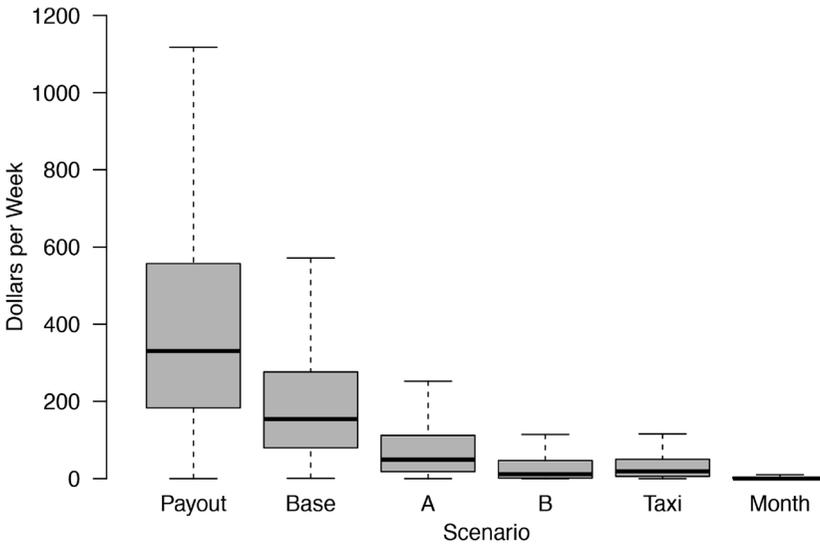


FIG. 12.—Expected labor surplus

shows box plots of the distribution of surplus over the various labor supply flexibility arrangements or scenarios outlined in Section VI.B. The box plot labeled “payout” is the expected total wages (in dollars/week) that drivers should have earned for each of the hours in which they were actually observed to supply labor. Note that the payout is net of all Uber fees, but gross of the driver’s car operating costs.

Our abstraction of the Uber-style arrangement in which drivers can pick whatever hour, day, and week they choose to work generates a large surplus of more than 40 percent of their total pay. This number may seem large. However, recall that the surplus in each hour the driver drives is definitionally at least weakly positive. If expected surplus for the hour is negative, the driver does not drive. As we showed in figure 10, only a small fraction of potential drivers are driving in any given hour, those with positive surplus. Here, we find that the median driver earns roughly \$21.67/hour, with a surplus of about \$10/hour, suggesting a reservation wage of \$11.67/hour. The reservation wage includes both the driver’s cost of time and also includes the costs of driving. Given the median trips per hour and trip length and using appropriate costs for a Toyota Prius (the modal Uber driver car in many of the largest cities), we estimate driving costs to be about \$3 to \$4 per hour.<sup>22</sup> This gives a net earning above the national minimum wage of \$7.25/hour but clearly below the minimum wage in some locations (the highest state-level minimum wage is \$11.50 in Washington state). Is this implied reservation wage too low to be plausible? We do not think it is, given that even earning minimum wage simply might not be feasible in the time windows that a particular driver has available to drive. If someone, for example, has a shift at a conventional job until 2:00 and has to pick up children from a day care that closes at 5:00, it is not clear what alternative job is actually available in that time frame. Additionally, for some set of people, driving may simply be more pleasant than alternative employment options.

Constraints on flexibility reduce surplus a great deal. For example, just the inability to adapt hour by hour within the same day (contrast case A with the base case) dramatically reduces surplus. If drivers are further restricted to be unable to adapt to both hourly and daily shocks (scenario B), surplus is further reduced but by a smaller factor than the hourly case. In other words, adaptation to the daily shock is less valuable to drivers than adaptation to hourly shocks. The taxi case allows drivers to respond to daily shocks but constrains them to work a full 8 hour shift. This results in a large

<sup>22</sup> Averages of trip distance and waiting time, etc., are found in Cook et al. (2018). An effective argument for a \$0.20/mile driving cost for a Prius is made by Campbell (2017). As Campbell points out, there are differential tax considerations for driving Uber as there are for wage labor. In particular, many Uber drivers drive efficient cars such as the Prius, and benefit from the federal deductibility of mileage at 53.5 cents per mile.

reduction in surplus over case A, where daily adaptation is possible but drivers do not have to work an entire shift.

Finally, precommitment to a month in advance reduces expected surplus to near zero for most Uber drivers. We should emphasize that commitment to a month in advance merely limits adaptation to weekly, daily, and hourly shocks but still allows for flexibility in the total quantity of hours worked and the allocation of that time worked over days of the week and hours of the day. It is not just a flexible work schedule, per se, that creates value to Uber drivers, but it is the ability to adapt to events that vary over time that is most valuable.

Figure 13 reports the distribution of expected labor supply for each of our proposed arrangements. It is clear that constraints on flexibility also reduce willingness to work. For example, the taxi constraint on adaptation to unpredictable shocks reduces labor supply from about 15 hours per week to less than 5 hours per week. This is, perhaps, not that surprising as our sample consists of drivers who have selected the Uber arrangement by choice over a taxi arrangement. However, there are many reasons a driver might prefer to be an Uber driver that are not related to flexibility, including a superior dispatching driver application with suggested driving routes, direct deposit of payments to a checking account, and the lower upfront cash requirements (no shift rental fee). What we have learned is that ability to adapt to shocks attracts Uber drivers and, without this adaptability, they will not participate much in this labor market.

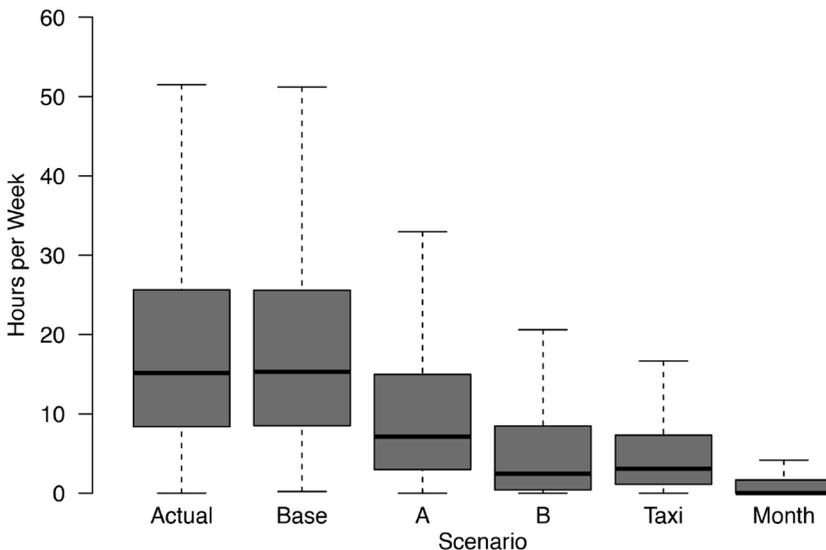


FIG. 13.—Expected labor supply

Table 4 provides more detail on the distribution of expected labor supply (top panel) and expected surplus (bottom panel). Of course, there is a distribution of surplus across drivers; some benefit much more than others from the Uber arrangement. At the median of the expected surplus distribution across drivers, the Uber arrangement (“base”) provides an expected surplus of \$154 per week, while simply turning off the ability to adapt to hourly shocks reduces surplus to less than one-third of that, about \$49 per week. Taxi arrangements are even worse, reducing surplus to one-eighth of the Uber base case (\$19 per week). Thus, a large fraction of the surplus that drivers gain derives from the flexibility.

We might expect that the value of the Uber arrangement should depend on the level of labor supply offered. If a driver is driving 50 or more hours per week, flexibility from day to day and hour to hour is limited almost by definition. The ability to opportunistically respond to high expected wage opportunities is also more limited for higher hour drivers, as evidenced by the lower labor supply elasticities measured for higher hour drivers in figure 11. Table 5 slices the expected surplus distribution based on decile of observed weekly labor supply. Comparing expected surplus in the base condition to payout, the fraction of payout that is

TABLE 4  
QUANTILES OF THE EXPECTED LABOR SUPPLY AND SURPLUS

LABOR SUPPLY						
QUANTILE	Actual	Expected				
		Base	A	B	Taxi	Month
.99	58.1	57.6	50.5	48.3	31.7	47.5
.95	44.6	44.0	33.7	28.7	19.5	24.8
.90	37.2	36.8	25.8	19.5	14.1	12.5
.75	25.6	25.6	15.0	8.5	7.3	1.7
.50	15.2	15.3	7.1	2.5	3.1	.0
.25	8.4	8.5	3.0	.4	1.1	.0
.10	4.8	4.9	1.2	.0	.4	.0
.05	3.5	3.5	.6	.0	.2	.0
.01	1.9	1.9	.1	.0	.0	.0
SURPLUS						
QUANTILE	Payout	Expected				
		Base	A	B	Taxi	Month
.99	1,311.7	777.7	472.5	359.7	263.8	279.8
.95	977.4	536.3	283.0	184.0	148.2	102.9
.90	811.1	428.3	207.6	118.5	102.1	44.3
.75	557.1	276.3	112.0	46.7	49.7	3.9
.50	330.3	154.1	49.1	11.6	18.7	.0
.25	183.2	79.7	18.3	1.7	5.8	.0
.10	105.9	42.5	6.4	.1	1.65	.0
.05	76.4	28.9	3.0	.0	.6	.0
.01	41.3	13.9	.5	.0	.0	.0

TABLE 5  
 EXPECTED SURPLUS BY LABOR SUPPLY DECILE

Decile	Labor Supply Range	Payout	Base	A	B	Taxi	Month
10	(37–104.6)	974.3	513.2	253.7	153.7	125.7	70.9
9	(29–37.2)	696.3	346.2	145.1	63.1	66.7	8.1
8	(23–28.7)	551.0	267.3	104.2	35.9	45.6	1.2
7	(19–23.0)	445.9	211.6	76.6	21.5	32.5	.0
6	(15–18.7)	362.6	169.4	58.2	13.7	23.7	.0
5	(12–15.2)	294.8	136.0	44.6	8.9	17.4	.0
4	(10–12.2)	236.3	106.9	32.3	5.2	12.1	.0
3	(7–9.6)	182.9	80.8	22.5	2.9	8.1	.0
2	(5–7.2)	132.3	56.2	13.7	1.3	4.6	.0
1	(0–4.8)	76.4	29.6	4.8	.2	1.4	.0

accounted for by surplus is surprisingly constant across labor supply deciles. The ability to pick off high-wage or low-reservation-wage hours does not lead low-hour drivers to capture a larger fraction of their payouts as surplus. Unsurprisingly, the destruction of surplus in moving from the base Uber arrangement to a taxi arrangement is more profound for lower hour drivers. Lower hour drivers get very little surplus in the taxi arrangement, largely because we estimate that they would not find it worth it to supply labor if they had to do so in 8 hour shifts. Nonetheless, it is remarkable that even drivers working more than 37 hours per week find the taxi arrangement to have an expected surplus of only one-quarter of the Uber arrangement. The ability to work split shifts and unconventional hour patterns in the Uber arrangement is still valuable for drivers in this group.

Our alternative scenario surplus calculations are designed to decompose the source of the labor surplus enjoyed by drivers under the Uber labor supply arrangement. That is, there are various dimensions of adaptation to shocks and lack of precommitment that contribute to the Uber surplus value, and we use our model to quantify the value of each. We hasten to add that we are not simulating a new equilibrium in the labor market under each scenario considered. For example, if the Uber arrangement were outlawed (as it has been in some communities) and only taxis remained, there would be a new equilibrium in the labor market with a new distribution of labor supply and different equilibrium wages from those observed in our data. Many, if not most, of the Uber drivers would withdraw from the market that meets consumer transportation demand and work elsewhere or not at all. Clearly, much of the labor surplus would be lost but there would be surplus gains for taxi drivers as taxi utilization and wages might increase as well as surplus obtained by Uber drivers in alternate jobs. We are not undertaking such a calculation, which would require a host of difficult-to-verify assumptions as well as detailed data on the labor supply decisions of taxi drivers.

Another limitation of our analysis is that our simplified alternative scenario analyses may not align fully with real-world employment

relationships. Workers in conventional jobs typically have some flexibility to adjust for shocks. That is, the worker can, when faced with a large and unusual shock, for example, likely call in sick. Thus, some conventional jobs may well be more flexible than our counterfactual examples. However, the literature cited above suggests that flexibility for low-wage, low-skilled jobs may be particularly limited. We have also shown that the great bulk of the labor surplus derives from adaptation to high-frequency (hourly) wage shocks. It is highly unlikely that a low-skilled worker would have the luxury of taking an hour off on a frequent basis. We should also point out that our shocks are symmetric. That is, adaptation to both positive and negative reservation wage shocks are possible in the Uber-style labor supply arrangement. A conventional work arrangement rarely allows workers to choose to work more if they unexpectedly find themselves short of cash. This is a very important aspect of the Uber arrangement that we believe is largely absent from conventional low-skilled labor arrangements.

In particular, it might be argued that our taxi scenario overstates the rigidity of the taxi arrangements that exist in the real world. While our taxi scenario allows drivers to adapt to daily (and weekly) shocks, we do not allow the driver to adapt to hourly shocks. For example, if, at the beginning of the day, the driver knows that he or she has an appointment in an hour later in that day, our taxi scenario considered above does not allow for adaptation in shift choice to avoid working in that hour. An alternative plausible scenario is one in which the driver foresees all hourly shocks at the time of making a shift choice. Intuitively, this should lead to higher surplus than our taxi scenario in that the driver cannot make any ex post errors in choosing a shift.

In order to explore this possibility, we considered an alternative taxi scenario in which the driver chooses shifts on the basis of realized hourly shocks.<sup>23</sup> That is, the driver still must pick at most one shift in a day and

<sup>23</sup> The driver observes the realizations of all hourly shocks and chooses whether to work and, if so, which shift to work on the basis of these realized shocks. Using the notation of Sec. VI.C, consider the decision to work shift 1, without loss of generality. The driver will work shift 1 if  $S_1 - S_2 = \delta_1 - \delta_2 - \sum_{t \in S_1} v_{h,t} - \sum_{t \in S_2} v_{h,t} \geq 0$ ,  $S_1 - S_3 = \delta_1 - \delta_3 - \sum_{t \in S_1} v_{h,t} - \sum_{t \in S_3} v_{h,t} \geq 0$ , and  $S_1 = \delta_1 - N_S v_w - N_S v_d - \sum_{t \in S_1} v_{h,t} \geq 0$ . Here  $S_j$  are the realized surpluses;  $S_j = \delta_j - N_S v_w - N_S v_d - \sum_{t \in S_j} v_{h,t}$ . Define the vector  $z' = (S_1 - S_2, S_1 - S_3, S_1)$ ;  $z \sim N(\mu, \Sigma)$  with  $\mu' = (\delta_1 - \delta_2, \delta_1 - \delta_3, \delta_1)$  and

$$\Sigma = \begin{bmatrix} (N_S + N_S)\sigma_h^2 & N_S\sigma_h^2 & N_S\sigma_h^2 \\ N_S\sigma_h^2 & (N_S + N_S)\sigma_h^2 & N_S\sigma_h^2 \\ N_S\sigma_h^2 & N_S\sigma_h^2 & N_S^2\sigma_w^2 + N_S^2\sigma_d^2 + N_S\sigma_h^2 \end{bmatrix}.$$

The probability of working shift 1 is  $\pi_1 = \int_{\mathbb{R}^{3+}} \phi(z|\mu, \Sigma) dz$ ;  $\phi(\cdot)$  is the multivariate-normal density. The expected surplus for working shift 1 given that shift 1 is chosen for work is  $E[S_1|\text{work}] = E[z_3|z \in \mathbb{R}^{3+}]$ . The total expected labor supply and total expected surplus can be easily computed using similar results for all shifts. See the appendix for computational details.

work the entire shift in our alternative taxi scenario, but the driver can avoid shifts with a large positive reservation wage shock in an hour. We used a random sample of 1,000 drivers (the same sample used in several analyses provided in Sec. VII) to compute expected labor supply and surplus using this alternative taxi scenario. Clearly, the surpluses computed under our alternative taxi scenario must, by definition, exceed the surpluses in the original taxi scenario. However, the real question is whether this new scenario reverses our qualitative conclusion that taxi-style shift arrangements reduce surplus dramatically. We find that, under the alternative taxi scenario, surplus increases by 51 percent over the original taxi surplus. However, even the new alternative arrangement affords a surplus dramatically lower than the Uber or case A arrangements. This alternative taxi arrangement has a median surplus less than one-fifth of the Uber arrangement and about 45 percent less than case A.

The analysis of this alternative taxi scenario is revealing because the scenario examined, while less flexible than Uber, is more flexible than most jobs. The worker can choose among three shifts each day with perfect foresight about any shocks to his or her willingness to work and can choose not to work any day that he or she chooses. The low surplus from this arrangement demonstrates the value that this (selected) sample of workers obtains from being able to work short shifts at unconventional frequency.

#### *E. Compensating Wage Differentials*

While we believe that a driver-by-driver estimate of expected labor surplus is ultimately the correct way to gauge benefits to Uber drivers from flexibility, the labor economics literature often considers the problem of computing compensating wage differentials. For example, we might want to estimate the increase in the wage rate that might be required to induce workers to work a nonstandard shift such as a weekend or night shift. Similarly, we can ask how much wages would have to increase in order to make individual Uber drivers indifferent between the Uber arrangement and various restricted scenarios in which adaptability to reservation wage shocks are limited.

Table 6 provides compensating wage differentials expressed as the multiple of wages required to make each driver achieve the same surplus from a more restrictive arrangement than the Uber base arrangement. Drivers that derive a large surplus from the flexibility afforded by the Uber arrangement will require very large increases in wages to offset the loss of surplus. Indeed, we see that very large compensating wage differentials are required. For example, the median driver requires a 54 percent increase in wages to be indifferent between the base Uber scenario and scenario A in which hourly adaptation is not allowed. The even more restrictive

TABLE 6  
COMPENSATING WAGE MULTIPLES

Quantile	A	B	Taxi
.99	8.39	>100	70.45
.90	2.72	56.45	7.56
.75	1.94	7.51	4.22
.50	1.54	2.78	2.79
.25	1.33	1.75	2.1
.10	1.23	1.42	1.74
.05	1.18	1.31	1.59
.01	1.13	1.19	1.39

scenario B does not allow drivers to adapt to either hourly or daily reservation wage shocks. We have seen that this reduces expected labor surplus to only a small fraction of the Uber arrangement. Accordingly, the median driver requires a very large increase of 178 percent in wages to make up for the lost surplus. The taxi arrangement has compensating wage differentials that are also very large.<sup>24</sup>

It should be emphasized that we are not computing a new labor market equilibrium wage for each scenario, but merely expressing the labor surplus in terms that some find more interpretable.

## VII. Sensitivity Analyses

In this section, we consider several sensitivity analyses performed to assess the role of model assumptions regarding the exogeneity of wages, the formation of wage expectations, our choice of hour block partitions, and the impact of competition from Lyft. In the appendix, we also consider the robustness of our analysis to prior settings.

### A. Exogeneity of Wages

We assume that our expected wage variable is exogenous to the labor supply decisions made on an hour-to-hour basis by drivers.<sup>25</sup> While there can be common demand shocks such as a concert or sporting event, this assumption rules out common supply shocks. A legitimate concern is that if there are common supply shocks of large magnitude, this can affect both the labor supply decisions of drivers as well as the prevailing expected wage. For example, if there were a large positive common supply shock

<sup>24</sup> Since the month in advance commitment scenario shuts down all adaptability, this would require a huge (and nearly infinite for some drivers) compensating increase in wages. For this reason, we did not think it useful to report the results of compensating wage differential calculations for the month commitment scenario.

<sup>25</sup> Frechette et al. (2016) make a similar assumption in the model of taxi driver labor supply used in their equilibrium simulations.

that raised reservation prices simultaneously for all drivers in a city, then we would expect falling overall labor supply and increasing wages, particularly in light of Uber's dynamic pricing policies, which are designed, in part, to remedy supply deficiencies. Thus, we would expect that if there were common supply shocks (both positive and negative), our model fitted under the exogeneity assumption would underestimate the responsiveness of drivers to changes in wages. Of course, the extent of this "endogeneity" bias would depend on the relative magnitudes of common supply shocks and idiosyncratic shocks to reservation wages.

To assess the importance of possible bias due to common supply shocks, we would ideally like some source of variation in wages that can be plausibly viewed as exogenous. If wages were varied randomly, this would be the ideal source of wage variation that is indisputably exogenous. Uber has, in the course of its business, conducted some randomized changes in wages on a limited basis in several cities. In the range of our data, one such set of changes was conducted in Orange County, California, during April 2016. A random sample of drivers received an email indicating that the driver would receive a 10 percent increase in wages for a 3 week period.<sup>26</sup> Another randomly selected group of drivers was selected for control purposes. The randomization was personally conducted by Keith Chen, who was then an employee of Uber, and it was conducted for Uber's business purposes. Approximately 3,000 drivers were assigned to both the "control" and "incentive" groups. In our analysis sample, we have 1,272 of the incentive group drivers and 1,240 of the control group.<sup>27</sup>

We exploit this source of exogenous variation to stress-test our model. We refit our model for each of the nonexperimental weeks in the incentive group and use these fitted coefficients to predict the response of drivers to the experimentally induced increase in incentives during the duration of the experiment. If our assumption of exogeneity of wages is incorrect and if there are large common shocks, we should expect that our model will underpredict the actual labor supply response to the increase in effective wage rate.

As in all field experiments, there are important implementation considerations. First, the incentive group could qualify for the 10 percent increase in earnings only on trips that originated in Orange County. If, for example, an Uber driver picked up a fare from Irvine (in Orange County) to Los Angeles International Airport, the driver would certainly try to pick up a return fare to maximize efficiency. The return trip would not qualify for the 10 percent incentive. This is a major issue for the Orange

<sup>26</sup> The same email offer was sent out once per week for a total of 3 weeks.

<sup>27</sup> Recall that we restrict attention to an active sample of drivers who work in at least 16 hours during our data set.

County market because of the close proximity to Los Angeles and many other separate Uber markets. In addition to restrictions on the origin of trips, the Uber incentive offer contained additional qualifications. Drivers had to “maintain a 90 percent acceptance and 25 percent completion rate over all hours online to qualify for this offer.” It is not clear how binding these constraints are on Uber drivers. In sum, the restrictions on the incentive condition in the Orange County incentive experiment mean that drivers effectively faced an incentive that could be considerably lower than 10 percent.

To assess the effective incentive rate, we exploit the fact that the Orange County experiment data show that, on average, drivers do not appear to have responded to increased incentives in the first week of the experiment.<sup>28</sup> In week 1, 1050 control drivers supplied 12,938 hours of labor or 12.32 hours per week on average, while 1063 incentive drivers supplied 13,060 hours or 12.28 hours per week.<sup>29</sup> That is, there was no aggregate response to the incentive. We can then use the payouts made to drivers to estimate the effective incentive rate. We regressed  $\log(\text{wages})$  on dummy variables for incentive eligibility and fixed effects for hour of day and week. We find that incentive eligible drivers earned a wage 2.3 percent higher than controls (standard error of .003). We will use this wage differential to predict labor supply for the remaining 2 weeks of the experiment.

Figure 14 compares actual labor supplied (in hours/week) with what is expected or predicted from our model fit to nonexperimental weeks (and using the estimated 2.3 percent increase in wages) for the 2 weeks of experimental data. We plot this separately for the control group of drivers versus treatment group. If there are no substantial biases in our model coefficient due to endogeneity, we should expect that controls and treated (incentive) group drivers would exhibit the same level of model fit. The two scatter plots are very similar.

However, it is possible that this model diagnostic based on true experimental variation is valid but of low discriminatory power due to the relatively small effective incentive of 2.3 percent. To assess the power of our diagnostic, we compare the predicted labor supply on experimental weeks under the assumption of a 2.3 percent increase in wages with the predicted labor supply with no increase in wages. Figure 15 provides a histogram of the difference in expected labor supply assuming a 2.3 percent increase in wages and a 0 percent increase. There is a discernible increase in labor supply predicted by our model from even this relatively small change in

<sup>28</sup> This is not uncommon with driver incentives at Uber and can be explained by inattention or delayed attention to emails. Drivers appear to first become widely aware of incentives at the end of an incentive's first week, when additional earnings appear on earnings statements.

<sup>29</sup> This is not significant.

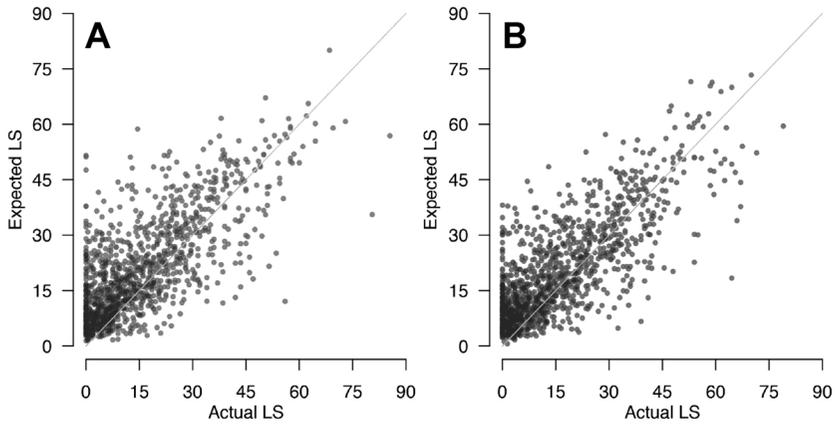


FIG. 14.—Expected versus actual labor supply (LS): Orange County experiment. *A*, Control. *B*, Treatment.

wage rates. This provides some validation that our diagnostic procedure has power in the relevant range of wage increases.

We conclude that possible biases due to common supply shocks are apt to be small relative to the labor supply changes predicted by our model.

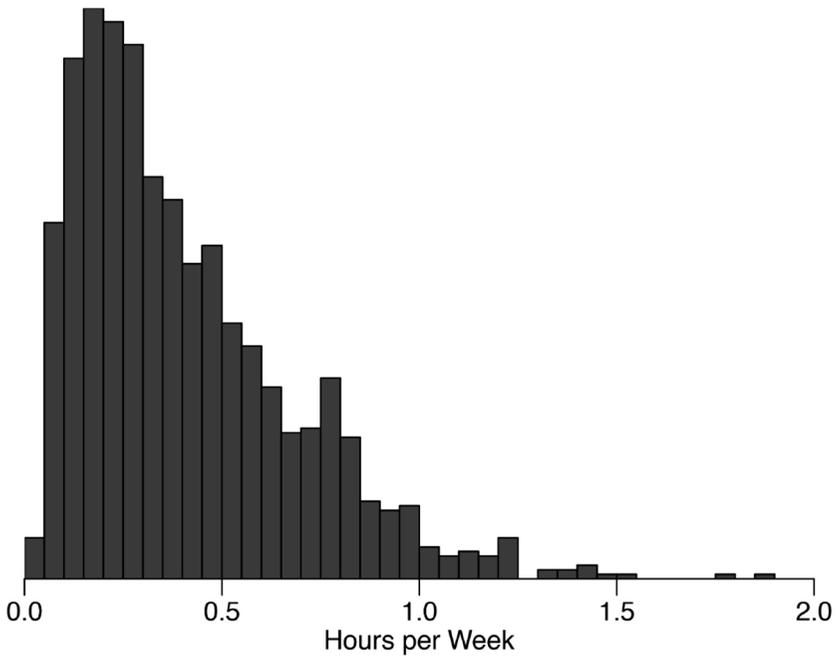


FIG. 15.—Difference in labor supply with and without wage incentives

### B. Formation of Expectations

In our model, we make an assumption of full information and rational expectations regarding wages. That is, we assume that drivers, in their decision making, use the expected wage for each unique city, week, and hour combination in our data. For example, if there is a week in which demand for transportation is high due to a convention in town, the drivers are assumed to be forward looking and to be able to estimate the implications for mean wages for that week. In addition, we assume that drivers anticipate that there might be different patterns of demand over the hours in different weeks. An example of this might be a concert that will increase demand on the night of that concert in a way that differs from other weeks.

We understand that this assumption assumes a high degree of both rationality and information gathering on the part of the drivers. We believe that our evidence of model fit shows that this assumption is reasonable. In this section, we consider an alternative and somewhat less-demanding assumption. We assume that drivers can form expectations of wage changes over weeks (within city) but do not forecast the pattern of demand to vary across weeks. This is implemented by estimating a scalar multiple by which the profile of expected wages is raised or lowered for each week. This multiple is estimated by a weighted average of the ratios of each week's wage by hour profile to the overall average for that city. This is implemented as follows:

$$\tilde{w}_{j,\text{wk}} = \rho_{j,\text{wk}} \bar{w}_j, \quad (20)$$

$$\rho_{j,\text{wk}} = \sum_{\text{hr}=1}^{168} \theta_{\text{hr}} \frac{w_{j,\text{wk},\text{hr}}}{\bar{w}_{j,\text{hr}}}. \quad (21)$$

Here  $j$  denotes modal city and  $\text{wk}$  denotes week;  $\bar{w}_j$  is a 168-dimensional vector of the mean wages for city  $j$  by hour averaged over all weeks in our data;  $\theta_{\text{hr}}$  are weights denoting the fraction of hours worked in hour of the week,  $\text{hr}$ , for all of our data (all cities and all weeks);  $\bar{w}_{j,\text{hr}}$  is the mean wage for city  $j$  in hour  $\text{hr}$  averaged over all weeks in our data.

Our assumption is that drivers are only partially rational in the sense that they only anticipate that some weeks will have higher or lower wages than others but that they cannot forecast how the pattern of wages by hour of the week will vary over weeks. Our intuition is that if drivers respond to the partially rational wages,  $\tilde{w}_{j,\text{hr}}$ , and not the fully flexible "full information rational expectations" wage profiles, then our model assuming fully rational expectations will underestimate labor supply elasticity and possibly overestimate the magnitude of the shocks to driver reservation wages. This would tend to overstate the surplus afforded by the flexible labor supply arrangement.

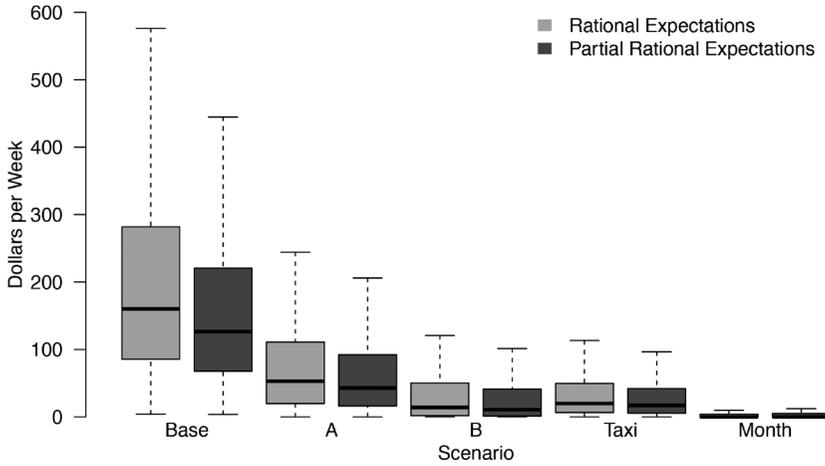


FIG. 16.—Labor surplus under different wage expectations

Figure 16 shows the distribution of estimated labor surplus for each of our flexibility scenarios. Note that because of computation constraints, the sensitivity analysis was conducted with a random sample of 1,000 drivers. The side-by-side box plots contrast the results assuming full rational expectations with what we are calling partial rational expectations. The differences between the surpluses calculated under different wage expectations are small, with the partial rational expectations process producing slightly smaller surpluses.

Table 7 shows the quantiles of the surplus distribution for partial and full rational expectations. While the surpluses are slightly smaller when we compare partial to full rational expectations, the ratio of surplus lost from more restrictive labor supply arrangements remains virtually unchanged. For example, consider the reduction from the base scenario

TABLE 7  
LABOR SURPLUS UNDER ALTERNATIVE WAGE EXPECTATIONS

QUANTILE	BASE		A		B		TAXI		MONTH	
	Full	Partial								
.99	768.5	656.9	486.1	392.3	325.6	257.6	272.4	228.5	270.6	219.7
.95	544.8	432.7	285.5	243.5	191.8	161.8	152.7	124.6	119.2	99.0
.90	430.6	337.6	215.6	176.4	126.8	104.6	110.4	92.6	51.6	47.5
.75	281.6	220.6	110.8	92.4	50.2	41.3	49.5	42.1	4.0	5.0
.50	160.3	126.6	52.9	42.9	14.0	10.7	19.9	17.1	.0	.0
.25	85.8	68.0	19.8	16.0	2.0	1.3	6.5	5.4	.0	.0
.10	48.7	35.9	7.2	5.6	.1	.0	1.6	1.4	.0	.0
.05	32.4	24.1	3.6	2.8	.0	.0	.7	.6	.0	.0
.01	13.3	10.2	.8	.8	.0	.0	.1	.1	.0	.0

to scenario A (no hourly adaptation). For full rational expectations, the surplus declines to 33 (52.9/160.3) percent of the base, while for partial rational expectations the decline is 33.9 percent.

It may be helpful to provide some intuition for why the surplus is lower if drivers have partial rational expectations yet the decline in surplus from the alternative constrained scenarios is similar whether drivers have full or partial rational expectations. One reason that surplus is lower under partial rational expectations is that a driver with a stable reservation wage will change her driving behavior if she knows that an hour will be particularly lucrative (or particularly unlucrative). Thus, a diminished ability to forecast the expected wages should lead to lower surplus, as we find. It is also possible that if drivers are only partially rational but we estimate the model assuming full rationality, we will systematically overestimate the value of the Uber scenario relative to alternative constrained scenarios because we will overestimate the magnitude of the driver's shock variances. Loosely, this is because we ascribe the driver's failure to drive in a particularly lucrative hour to a reservation wage shock, when in fact it is due to the driver's ignorance of the hourly wage. However, our robustness results suggest that this second issue is not extremely important. While the base case surplus is lower when we assume partial forecasting ability by the drivers, the ratio of the base case surplus to that of the alternative scenarios is very similar to the results that we obtain assuming full driver rationality.

### *C. Fineness of Hour Blocks*

In our empirical model, we partition the week into nine blocks of hours in order to make the estimation tractable. One concern with this procedure is that if we group hours into a single block for which individual drivers have consistently heterogeneous reservation wages, we will likely estimate very large shock variances. These large shock variances will have implications for our surplus estimates. To explore this concern, we undertake a robustness exercise using our robustness subsample of 1,000 drivers. We reestimate reservation wage parameters using 12 different hour blocks in the week rather than nine. In subdividing our original nine blocks, our goal was to subdivide blocks for which our model-free evidence suggests that different drivers were systematically more likely to drive in specific hours within the block. For example, our model-free evidence suggests that starting and stopping driving are common midmorning on weekdays, rendering the Monday–Friday 7 a.m. to noon block a good candidate for subdivision. We created three new blocks. Specifically, we subdivided the Monday–Friday 7 a.m. to noon block into two blocks, one from 7 a.m. to 9 a.m. and the other from 10 a.m. to noon. Next, we subdivided the Friday and Saturday evening block into a separate Friday evening block and a Saturday

evening block. Third, we took the two weekday afternoon and rush hour blocks and subdivided them into three blocks. In place of a 1–4 p.m. block and a 5–8 p.m. block, we allowed separate parameters for a 1–3 p.m. block, a 4–6 p.m. block and a 7–8 p.m. block.

Figure 17 shows the distribution of estimated labor surplus for “standard blocking” (our original nine blocks) and the “alternative blocking” with finer hour block partitions. The results are surprisingly similar to our original surplus estimates for both the base case and the alternative scenarios. The results show very slightly lower weekly surpluses under the finer partitions of the weekly hours; the surplus calculations for the alternative scenarios remain very similar to our original estimates.

*D. Presence of Competing Platforms*

Another potential concern with our results may be the extent to which they are impacted by the possibility that drivers are multihoming between Uber and Lyft, a competing platform. Here, we discuss some theoretical reasons why multihoming may not be a concern for our estimates. Then, we show results in which we estimate our model separately for Houston, Texas. Due to regulatory action, during the time period of our sample, Uber offered service in Houston, Texas, but Lyft did not.

As we discussed before, many of the drivers in our study are not simply making choices between driving Uber and leisure. Many drivers are

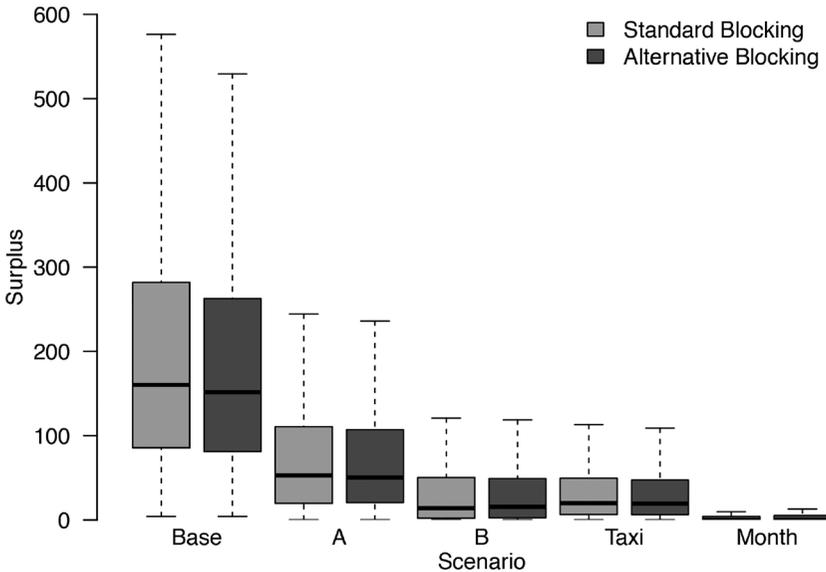


FIG. 17.—Labor surplus with alternative (finer) hour blocking

engaged in other economic activities such as home production and working at other jobs. Thus, a driver's reservation wage in any hour should be interpreted as taking into account these alternative economic activities. In this way, we do not believe that Lyft is particularly different from the other alternative activities facing drivers. We cannot observe these other activities, including Lyft, directly.

One way in which the presence of Lyft can be concerning is if Lyft creates important common supply shocks across drivers. As we have already discussed, common supply shocks are a threat to our identification strategy, and the Orange County analysis discussed above is designed to address these concerns. Another strategy to address these concerns is to examine the performance of our model in a location where Lyft does not operate. Clearly, there is not exogenous variation in where Uber and Lyft operate. However, we believe that the case of Houston is helpful to examine. Lyft (but not Uber) exited the Houston market in 2014 when the Houston city council passed a set of regulations impacting ride-sharing companies. Uber (but not Lyft) similarly exited Galveston following the passage of city regulations. Both reentered those markets in 2017 following action by the state legislature.

We examine our model focusing entirely on Houston. We include in our sample all drivers whose modal driving city is Houston (and who otherwise meet the inclusion criteria specified in Section V. Payouts and surplus are slightly higher in Houston than they are on average in the other cities excluding Houston. As illustrated by figure 18, the decline in surplus

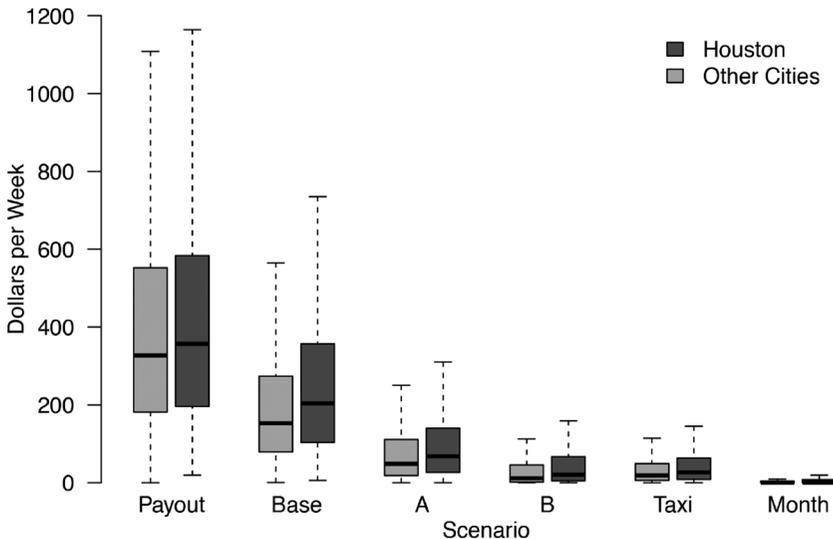


FIG. 18.—Labor surplus in Houston versus other cities

resulting from our alternative scenarios is very similar to the results that we obtain for other cities. Thus, we have no reason to believe that common supply shocks or other econometric issues caused by the existence of Lyft are importantly problematic for our results.

### VIII. Conclusions

The Uber driver arrangement attracted more than a million drivers to offer labor supply during the 8 month period of our data, which is limited to only the US UberX service. One of the attractions of Uber is the flexibility afforded to drivers. Not only can drivers choose to supply relatively small numbers of hours per week, but they can also allocate these hours flexibly over the days and hours of the week. However, this is not the only or even most important source of flexibility provided to Uber drivers. Another important source of flexibility is the ability of an Uber driver to adapt on an hour-by-hour basis to changes in demands on her time. While traditional workplaces do compete to provide flexibility to workers, the literature suggests that lower wage, lower skill workers typically have limited ability to respond to everyday shocks. The goal of this paper is to estimate a model of labor supply that will allow for a quantification of the value of both flexibility and adaptability.

We postulate a model in which each driver has a reservation wage process with both a predictable mean component as well as weekly, daily, and hourly shocks. This operationalizes the view that workers face unpredictable events that can change their labor supply decisions on an hourly basis. We assume that drivers form rational expectations regarding the expected wage and make labor supply decisions on an hour-by-hour basis by comparing their own reservation wage to the prevailing expected wage. Our model is a multivariate probit model with a time-varying censoring point that facilitates a greater degree of identification than the traditional probit structure. Driver-level exact finite sample inference is possible using a hybrid MCMC approach.

We estimate large labor supply elasticities exceeding 1.5 for most drivers and on the aggregate level. We also estimate very large shock variances, suggesting the potential for large driver surplus in Uber-like arrangements that allow drivers to decide, on an hour-by-hour basis, when to work. We compute driver labor surplus—accounting for 40 percent of total expected earnings, or \$150 per week on average—under the existing Uber arrangement. Labor surplus for alternative work arrangements, which limit drivers' ability to adapt to hourly and daily reservation wage shocks, are also computed. Constraints on the ability to adapt to shocks have large effects on expected labor surplus; eliminating this ability reduces labor surplus by more than two-thirds. We also consider a taxi-style arrangement in which drivers can decide on a daily basis whether or not to work

and which of three shifts to work but must work an entire 8 hour shift. The taxi arrangement reduces expected labor surplus to one-eighth of the Uber arrangement.

We also calculate the compensating wage differentials necessary to make drivers indifferent between the highly adaptable Uber arrangement and more restricted arrangements. To compensate for the inability to adapt to hourly reservation wage shocks, increases in wages of more than 50 percent would be required. For the taxi arrangement, the median driver would require almost a doubling of wages in order to compensate for reduced adaptability.

In summary, we document an important source of value in flexible work arrangements—the ability to adapt work schedules to time-varying reservation wages. Perhaps not surprisingly, this adaptability has high value to individuals who have selected into the Uber platform. Our expectation is that technology will enable the growth of more Uber-style work arrangements. While such arrangements may have important downsides relative to the traditional careers they supplant or supplement, we expect that flexibility will be an important source of value in such arrangements.

## References

- Altonji, Joseph G., and Christina H. Paxson. 1988. “Labor Supply Preferences, Hours Constraints, and Hours-Wage Trade-Offs.” *J. Labor Econ.* 6 (2): 254–76.
- Altonji, Joseph G., and Emiko Usui. 2007. “Work Hours, Wages, and Vacation Leave.” *ILR Rev.* 60 (3): 408–28.
- Board of Governors of the Federal Reserve System. 2016. “Report on the Economic Well-Being of U.S. Households in 2015.” <https://www.federalreserve.gov/2015-report-economic-well-being-us-households-201605.pdf>.
- Bond, James T., and Ellen Galinsky. 2011. “Workplace Flexibility and Low-Wage Employees.” <https://familiesandwork.org/downloads/WorkFlexandLowWageEmployees.pdf>.
- Buchholz, Nicholas. 2015. “Spatial Equilibrium, Search Frictions, and Efficient Regulation in the Taxi Industry.” Working paper, Dept. Econ., Univ. Texas, Austin.
- Camerer, Colin, Linda Babcock, George Loewenstein, and Richard Thaler. 1997. “Labor Supply of New York City Cabdrivers: One Day at a Time.” *Q. J. E.* 112 (2): 407–41.
- Campbell, Harry. 2017. “How to Calculate Per Mile Earnings instead of Per Hour.” <https://therideshareguy.com/how-to-calculate-per-mile-earnings-instead-of-per-hour>.
- . 2018. “The Rideshare Guy 2018 Reader Survey.” [https://docs.google.com/document/d/1g8pz00OnCb2mFj\\_97548nJAj4HfluExUEgVb45HwDrE/edit](https://docs.google.com/document/d/1g8pz00OnCb2mFj_97548nJAj4HfluExUEgVb45HwDrE/edit).
- Chetty, Raj. 2012. “Bounds on Elasticities with Optimization Frictions: A Synthesis of Micro and Macro Evidence on Labor Supply.” *Econometrica* 80 (3): 969–1018.
- Cook, Cody, Rebecca Diamond, Jonathan Hall, John List, and Paul Oyer. 2018. “The Gender Earnings Gap in the Gig Economy: Evidence from over a Million Rideshare Drivers.” Working paper, Graduate School Bus., Stanford Univ.

- Council of Economic Advisors. 2010. "Work-Life Balance and the Economics of Workplace Flexibility." [https://digitalcommons.ilr.cornell.edu/key\\_workplace/714](https://digitalcommons.ilr.cornell.edu/key_workplace/714).
- Cramer, Judd, and Alan B. Krueger. 2016. "Disruptive Change in the Taxi Business: The Case of Uber." *A.E.R.* 106 (5): 177–82.
- Farber, Henry S. 2005. "Is Tomorrow Another Day? The Labor Supply of New York City Cabdrivers." *J.P.E.* 113 (1): 46–82.
- . 2015. "Why You Cannot Find a Taxi in the Rain and Other Labor Supply Lessons from Cab Drivers." *Q.J.E.* 130 (4): 1975–2026.
- Farrell, Diana, and Fiona Greig. 2016a. "Paychecks, Paydays, and the Online Platform Economy: Big Data on Income Volatility." <https://www.jpmorganchase.com/corporate/institute/document/jpmc-institute-volatility-2-report.pdf>.
- . 2016b. "The Online Platform Economy: Has Growth Peaked?" <https://www.jpmorganchase.com/corporate/institute/document/jpmc-institute-online-platform-econ-brief.pdf>.
- Frechette, Guillaume R., Alessandro Lizzeri, and Tobias Salz. 2016. "Frictions in a Competitive, Regulated Market: Evidence from Taxis." Working paper, Dept. Econ., New York Univ.
- Golden, Lonnie. 2015. "Irregular Work Scheduling and Its Consequences." Working paper, Economic Policy Inst.
- Gustafson, Krystina. 2016. "On-Call Scheduling Debate: Where Retailers Stand." <https://www.cnbc.com/2016/02/04/on-call-scheduling-debate-where-retailers-stand.html>.
- Hall, Jonathan V., and Alan B. Krueger. 2016. "An Analysis of the Labor Market for Uber Driver-Partners in the United States." Working Paper no. 22843 (November), NBER, Cambridge, MA.
- Hamermesh, Daniel S. 1999. "The Timing of Work over Time." *Econ. J.* 109 (452): 37–66.
- Katz, Lawrence F., and Alan B. Krueger. 2016. "The Rise and Nature of Alternative Work Arrangements in the United States, 1995–2015." Working Paper no. 22667 (September), NBER, Cambridge, MA.
- Keane, Michael, and Richard Rogerson. 2015. "Reconciling Micro and Macro Labor Supply Elasticities: A Structural Perspective." *Ann. Rev. Econ.* 7 (1): 89–117.
- Kostiuk, Peter F. 1990. "Compensating Differentials for Shift Work." *J.P.E.* 98 (5): 1054–75.
- Lagos, Ricardo. 2003. "An Analysis of the Market for Taxicab Rides in New York City." *Internat. Econ. Rev.* 44 (2): 423–34.
- Lale, Etienne. 2015. "Multiple Jobholding over the Past Two Decades." Working paper, Bur. Labor Statis.
- Mas, Alexandre, and Amanda Pallais. 2016. "Valuing Alternative Work Arrangements." Working Paper no. 22708 (September), NBER, Cambridge, MA.
- Oettinger, Gerald S. 1999. "An Empirical Analysis of the Daily Labor Supply of Stadium Vendors." *J.P.E.* 107 (2): 360–92.
- Oyer, Paul. 2016. "The Independent Workforce in America: The Economics of an Increasingly Flexible Labor Market." Working paper, Graduate School Bus., Stanford Univ.
- Paxson, Christina H., and Nachum Sicherman. 1996. "The Dynamics of Dual Job Holding and Job Mobility." *J. Labor Econ.* 14 (3): 357–93.
- Rebitzer, James B., and Lowell J. Taylor. 1995. "Do Labor Markets Provide Enough Short-Hour Jobs? An Analysis of Work Hours and Work Incentives." *Econ. Inquiry* 33 (2): 257–73.

- Renna, Francesco, and Ronald Oaxaca. 2006. "The Economics of Dual Job Holding: A Job Portfolio Model of Labor Supply." IZA Discussion Paper no. 1915, Inst. Study Labor, Bonn. Available at SSRN: <https://ssrn.com/abstract=877897>.
- Reynolds, Jeremy. 2004. "When Too Much Is Not Enough: Actual and Preferred Work Hours in the United States and Abroad." *Sociological Forum* 19:89–120.
- Senesky, Sarah. 2005. "Testing the Intertemporal Labor Supply Model: Are Jobs Important?" *Labour Econ.* 12 (6): 749–72.

## A Estimation Method and Convergence Properties

### A.1 MCMC Method

Given our specification of the reservation wage process, our goal is to make driver-level inferences regarding the parameters of the mean reservation wage function and the standard deviation of the three error components. These parameters will allow us to compute the amount of surplus each driver can expect to receive from the Uber labor supply arrangement. To fix notation, we write the reservation wage process as

$$w_i^* = X_i\beta_i + \varepsilon_i$$
$$\varepsilon_i \sim N(0, \Omega(\sigma_i))$$

Here  $\sigma_i^t = (\sigma_{w,i}, \sigma_{d,i}, \sigma_{h,i})$ . The  $X$  matrix contains dummies that allow the mean reservation wage to vary for each of our nine defined hour blocks. The variance-covariance matrix for shocks to reservation wages is populated according to our error component model (3) with the standard deviations for each shock. Thus, our goal is to provide a procedure which will deliver inferences for each of 12 parameters for each of our 197,000 drivers. We adopt a Bayesian approach which is the only feasible approach for models which have likelihoods involving high dimensional integrals.

Given that the likelihood function cannot be directly evaluated, we utilize data augmentation. For each driver, we augment the 12 mean and variance parameters with the vector of unobserved reservation wages as has become standard in the treatment of either the Multinomial Probit or Multivariate Probit models.<sup>1</sup> The key insight is that given the reservation wages, inference for the  $\beta$  and  $\sigma$  parameters is straightforward, involving either standard Bayesian treatment of regression for the mean function parameters or a random walk in only three dimensions for the  $\sigma$  parameters.

---

1. See Rossi et al. (2005), 4.2-4.3, for example.

Our MCMC algorithm is a hybrid “Gibbs-style” method which cycles through three sets of simulations – two of which are standard Gibbs sampler draws comprised of one-for-one draws from conditional posteriors and one of which is a random-walk Metropolis draw. Combining all three sets of draws creates a continuous state-space Markov process which has the posterior distribution for driver  $i$  as its equilibrium distribution.<sup>2</sup>

$$w_i^* | X_i, w_i, y_i, \beta_i, \sigma_i \quad (1)$$

$$\beta_i | w_i^*, X_i, \sigma_i \quad (2)$$

$$\sigma_i | w_i^*, X_i, \beta_i \quad (3)$$

In the Bayesian treatment of linear models with error components, it is common to introduce each of the random effects as parameters.<sup>3</sup> Here we have random effects corresponding to each of the weeks and days that we observe driver  $i$ . In our setting, it would be appropriate to impose a zero mean restriction on the random effects so that we can interpret them as a shock. The alternative to this approach is to integrate out the random effects, by using a correlated error term. Our experimentation with the approach which augments with the random effects is that the associated Markov chain is very highly autocorrelated. Since we have no direct use for estimates of the driver specific random week and day effects, we prefer the approach that integrates them out. This requires a random walk step instead of a pure Gibbs sampler (conditional on the draw of the reservation wage vector). However, our random walk step is only in three dimensions and performs remarkably well.

### Draw of Reservation Wage

(1) could be accomplished by a direct draw from a truncated multivariate normal for each week of the driver data. There is no method which can efficiently draw from a truncated

---

2. We used 10,000 draws for each of the 197,000 drivers with a burn-in of 2500 draws. The driver models were estimated using the Comet supercluster at UCSD. This cluster allowed us to use 768 nodes which allowed us to perform all MCMC draws in less than one day of computing.

3. See, for example, Gelfand et al. (1995).

168-dimensional normal distribution. Instead, we employ the Gibbs sampler of McCulloch and Rossi (1994) to “Gibbs-thru” each element of the reservation wage vector using univariate normal draws (see equation 4.2.5 of Rossi et al. (2005) for details). These univariate draws are either truncated from below or above depending on the value of the labor supply indicator variable (truncated from above by the wage if  $y = 1$  and from below by the wage if  $y = 0$ ). The mean and variances of the truncated normal distribution can be obtained from  $X\beta$  and the inverse of the weekly covariance matrix,  $\Omega_w$ . The weekly covariance matrix of the error components is easily computed from  $\sigma$  using the eigenvalue, eigenvector decomposition of  $\Omega_w$  as shown below in equation (13), (15),(16).

The standard inverse CDF method cannot be used to draw the univariate truncated normal draws because of the possibility of draws in the extreme tails of the normal distribution and possible numerical errors and overflows. Truncated normal draws were made with a three part method that depends on where the truncation point ( $w_{it}$ ) is relative to the center of the normal distribution. The algorithm breaks the draw problem into three regions (defined here in terms of truncation from above); 1: if the truncation point is more than 4 standard deviations above the mean, then normal based rejection sampling is done, 2: if the truncation point is within  $\pm 4$  standard deviations from the mean, then an inverse CDF method is used, and finally 3: if the truncation point is more than 4 standard deviations below the mean then rejection sampling based on an exponential envelope is used.

### **Draw of $\beta$**

Given the draw of the latent reservation wage vector and  $\Omega_w$ , the draw of the  $\beta$  parameter which provides different means for different hour-blocks can be accomplished by a standard Bayesian analysis of a regression model with a known variance covariance matrix. We assume

a standard normal prior for  $\beta$ .

$$\beta \sim N(0, A) \quad (4)$$

$$A = \text{diag}(0.01, 0.1\iota_8) \quad (5)$$

The notation,  $\text{diag}(\text{vec})$ , means to form a diagonal matrix with  $\text{vec}$  as the diagonal. The setting of  $A$  is a very diffuse prior on the element of the intercept (overall mean reservation wage) coupled with tighter priors on the mean reservation wages for each hour-block. This is a conservative choice of prior in that it puts low probability on situations in which very large excesses of wages over reservation wage (large surplus) are possible. Given  $\sigma$ , we are able to compute the variance-covariance matrix

of the error terms on a week by week basis using (3). This matrix can be used to transform the regression equation into a equation with uncorrelated and unit variance error terms. The posterior for this transformed system is given by

$$\beta|X, w^*, y, \sigma \sim N\left(\tilde{\beta}, \left(\tilde{X}^t \tilde{X} + A\right)^{-1}\right) \quad (6)$$

with  $\tilde{\beta} = \left(\tilde{X}^t \tilde{X} + A\right)^{-1} \left(\tilde{X}^t \tilde{w}^*\right)$ ,  $\tilde{w}^* = Hw^*$ , and  $\tilde{X} = HX$ .  $H$  is the root of the inverse of the covariance matrix of the error terms.

$$\Sigma = \text{Var}(\varepsilon) = \text{diag}\left(\Omega_{w_1}, \dots, \Omega_{w_{N_i}}\right) \quad (7)$$

$$\Sigma^{-1} = HH^t = \text{diag}\left(H_{w_1}H_{w_1}^t, \dots, H_{w_{N_i}}H_{w_{N_i}}^t\right) \quad (8)$$

Here  $\Omega_{w_j}$  is the variance-covariance matrix of week  $j$  in driver  $i$ 's work history ( $N_i$  is the number of weeks we observe driver  $i$ ). (3) provides the formula for each driver-week's covariance matrix. Each of these matrices can easily be computed from knowledge of  $\sigma$  and the number of days in each week.

## Draw of $\sigma$

The draw of each of the three variance components in (3) is accomplished by a random-walk Metropolis step. Since each of sigmas must be positive, we reparameterize as  $\tau^t = \log(\sigma^t)$ . We assume that each of the three taus has an independent and normal prior. This means that we are assuming, a priori, each of the variance components is independent and log-normally distributed.

$$\sigma_j \sim \exp\left(N\left(\mu_{\lnsigma}, \sigma_{\lnsigma}^2\right)\right), j = w, d, h \quad (9)$$

$\mu_{\lnsigma} = 1$  and  $\sigma_{\lnsigma}^2 = .5$ . This a relatively tight prior that shrinks each of the variance components towards 0. Again, this is a conservative choice which reduces surplus as large values of the reservation wage variance yield greater surplus in a flexible work arrangement.

Given the log-normal prior on  $\sigma$ , we implement a standard random-walk Metropolis method for drawing  $\tau = \log(\sigma)$ . The likelihood function is simply the product of  $N_i$  multivariate normal distributions (one for each week). Each normal distribution has a mean extracted from  $X_i\beta$  and variance-covariance matrix determined by the number of days in each week and the current value of  $\sigma$ . Candidate values of  $\tau$  are drawn as follows:

$$\tau_c = \tau_{old} + s_{R\&R} R_{inc}^t v \quad (10)$$

$$v \sim N(0, I) \quad (11)$$

$s_{R\&R} = \frac{2.93}{\sqrt{3}}$  is the scaling constant of Roberts and Rosenthal (2001). The RW increments variance covariance matrix is chosen to approximate the diagonal of the inverse of the negative Hessian of the log-likelihood. Experimentation with different values of the  $\sigma$  vector show that the Hessian is remarkably stable on a weekly basis and we take

$$R_{inc} = \frac{1}{\sqrt{N_i}} \text{diag}(1, 0.3, 0.05) \quad (12)$$

**Efficient Computation of Covariance Structures** In order to perform the draw of  $w^*$  (1) and the draw of  $\beta$  (2), we must have an efficient way of computing the inverse of variance-covariance matrix of the error term. As shown in (8), the error covariance matrix depends only on the number of days in each week of the driver's work history and the three variance components parameters. We use the eigenvector, eigenvalue decomposition of the week covariance matrix to achieve this efficiently.<sup>4</sup>

$$\Omega_w = Q\Lambda Q^t \quad (13)$$

Here  $Q$  is an  $(nd * 24) \times (nd * 24)$  orthogonal matrix of normalized eigenvectors and  $\Lambda$  is a diagonal matrix of of the  $nd * 24$  eigenvalues. In order to perform the draws required, we need the root of the inverse of this matrix.

$$\Omega_w^{-1} = Q\Lambda^{-1}Q^t = HH^t; H = Q\Lambda^{-\frac{1}{2}} \quad (14)$$

The key to efficient computation of  $H$  is that the matrix of eigenvectors does not depend on  $\sigma$ , only the eigenvalues in the depend on  $\sigma$ . Both the eigenvectors and eigenvalues depend the number of days in the week. Given that there are only 7 possibilities for the number of days in a week, we precompute the matrices of eigenvectors and store them in a container. As we draw new values of  $\sigma$ , we simply use the old matrices of eigenvectors and update the eigenvalues. The eigenvalues are given by the formulae

$$\begin{aligned} \lambda_1 &= (24 \times nd) \sigma_w^2 + nh\sigma_d^2 + \sigma_h^2 \\ \lambda_2 \dots \lambda_{nd} &= nh\sigma_d^2 + \sigma_h^2 \\ \lambda_{nd+1} \dots \lambda_{nd \times 24} &= \sigma_h^2 \end{aligned} \quad (15)$$

The eigenvectors (note: these are presented un-normalized to preserve the intuition of

---

4. We thank A. Ronald Gallant for the suggestion to use the eigenvalue, eigenvector decomposition.

how they are derived) can be thought of grouped into one “overall” eigenvector,  $nd - 1$  “across-day” eigenvectors, and  $nd \times (24 - 1)$  “within-day” eigenvectors

$$E = [e_1 | E_A | E_W] \tag{16}$$

$$e_1 = \iota_{nd \times 24}$$

$$E_A = F_A \otimes \iota_{24}$$

$$E_W = I_{nd} \otimes F_W$$

with

$$F_A = \begin{bmatrix} 1 & 1 & & 1 \\ -1 & 1 & & 1 \\ 0 & -2 & \cdots & \\ \vdots & 0 & & \vdots \\ & \vdots & & \\ 0 & 0 & & -(nd - 1) \end{bmatrix}$$

and

$$F_W = \begin{bmatrix} 1 & 1 & & 1 \\ -1 & 1 & & 1 \\ 0 & -2 & \cdots & \\ \vdots & 0 & & \vdots \\ & \vdots & & \\ 0 & 0 & & -(24 - 1) \end{bmatrix}.$$

## A.2 Convergence and Acceptance rates

Our MCMC procedure shows excellent convergence and fit properties. A RW Metropolis chain with poorly tuned increment density will exhibit either slow navigation because of steps that are smaller than optimal or high autocorrelation because of high rejection rates. Figure 1 shows a histogram of acceptance rates. For a normal target, an acceptance rate of

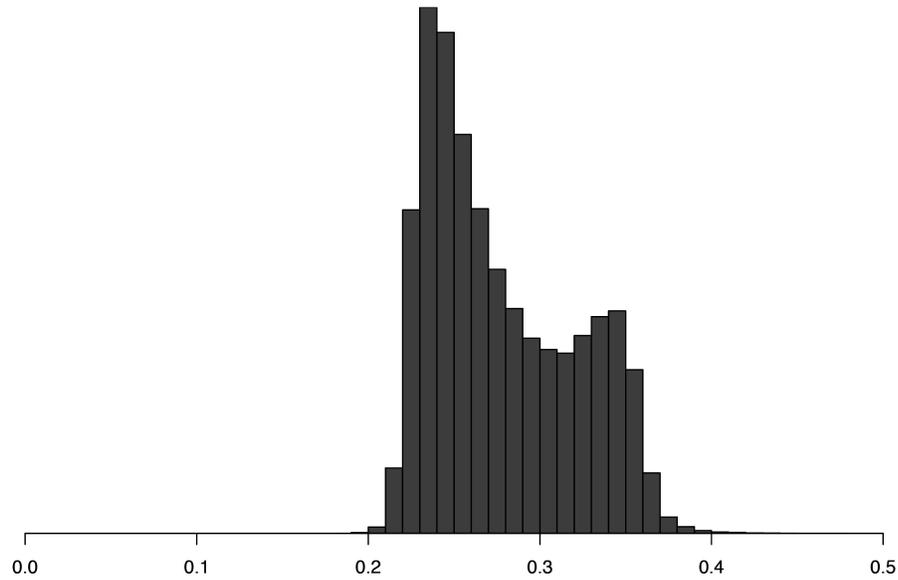


Figure 1: RW Acceptance Rates

30 percent is optimal. Our chain shows a very tight distribution of acceptance rates near 30 percent.

### A.3 Robustness to Prior Sensitivity

The prior we use in our analyses is a relatively diffuse prior but still more informative than is typically used. In many Bayesian analyses, extremely diffuse “default” priors are used. The emphasis in typical Bayesian applications is inference regarding model parameters. Our emphasis is on estimated labor surplus which is a complicated function of the distribution of model parameters over drivers. We use a tighter prior than typical analyses in order to obtain conservative estimates of the extent of labor surplus. Large values of the reservation wage parameters would typically be associated with higher levels of surplus. For example, the prior on  $\sigma$  shown in (9) shrinks the estimates of the shock standard deviations toward zero. Smaller shock sizes will lower the value of flexibility. Similarly, the prior on the mean reservation wage parameters is designed to shrink away from higher values of surplus. We

do not shrink the intercept in the mean reservation wage parameters but we do shrink the “slopes” or differences in mean reservation wages toward zero which reduces the labor surplus generated by periods with low mean reservation wage. Of course, all priors will be dominated by the data in situations where there large amounts of informative data. Most drivers in our dataset are observed for 5000 or more hourly observations; however, there is a small subset (those drivers that worked only a short interval of time in our data) where there number of hourly observations is in the 1000 to 2000 range. For these drivers, our priors serve to reduce outlying parameter estimates which might be associated with erroneously high labor surpluses.

We explore more diffuse prior settings and gauge the impact of these “looser” prior settings on the distribution of estimated labor surplus. We employ four basic sets of prior settings. Recall that the priors are of the form:

$$\beta \sim N(0, A^{-1})$$
$$\sigma_j \sim iid \exp(N(\mu_{lnsigma}, \sigma_{lnsigma}^2))$$

**Default:**  $diag(A)^t = (.01, .1, \dots, .1)$ ,  $\mu_{lnsigma} = 1$ , and  $\sigma_{lnsigma}^2 = .5$

**Loosen\_Beta:**  $diag(A)^t = (.01, .05, \dots, .05)$ ,  $\mu_{lnsigma} = 1$ , and  $\sigma_{lnsigma}^2 = .5$

**Loosen\_Sigma:**  $diag(A)^t = (.01, .1, \dots, .1)$ ,  $\mu_{lnsigma} = 3$ , and  $\sigma_{lnsigma}^2 = 2$

**Loosen\_Both:**  $diag(A)^t = (.01, .05, \dots, .05)$ ,  $\mu_{lnsigma} = 3$ , and  $\sigma_{lnsigma}^2 = 2$

Figure 2 shows the distribution of expected labor surplus for the base case with each of the four priors above. As expected the more diffuse priors shift the distribution of expected labor surplus to somewhat higher values. It does appear that, within a reasonable range, our results are not overly sensitive to the prior distributions used. Note that all computations regarding prior sensitivity are performed on a random sample of 1000 drivers in order to reduce computational demands.

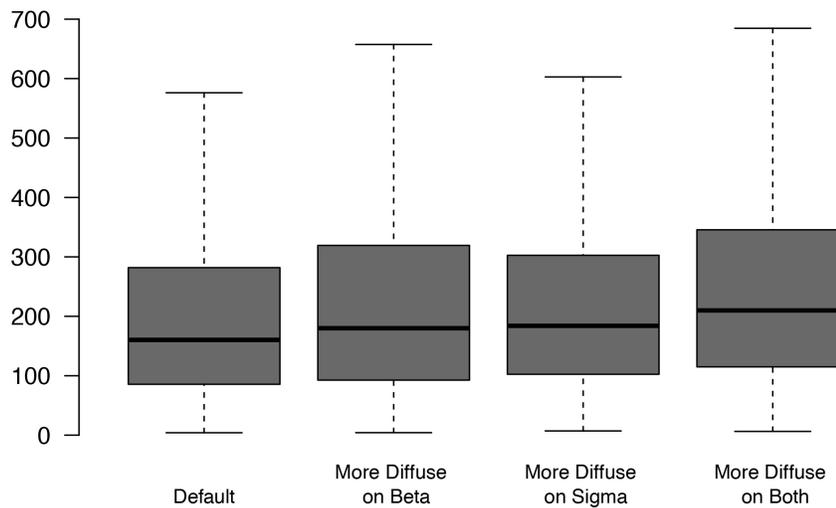


Figure 2: Prior Sensitivity for Expected Labor Surplus

#### A.4 Alternative “Taxi” Scenario Calculations

As discussed in section 6.4, we considered a more flexible version of the “taxi” scenario in which drivers are still required to choose one shift to work and must still work all hours in that shift but they can adapt to the hourly shocks in the choice of shift. In this section, we provide the basis for these calculations.

We assume that the driver observes the realizations of all 24 hourly shocks. Therefore, the driver chooses whether to work and, if so, which shift to work on the basis of these realized shocks. To calculate the probability that the driver works and the probability of working each shift as well as the expected surplus given the decision to work that shift, we must evaluate integrals of a trivariate correlated multivariate normal distribution. In this appendix, we will consider the case of three shifts but the results generalize trivially. Using the notation of section 6.3, consider the decision to work shift 1, without loss of generality.

The driver will work shift 1 if

$$\begin{aligned}
 S_1 - S_2 &= \delta_1 - \delta_2 - \sum_{t \in S_1} v_{h,t} - \sum_{t \in S_2} v_{h,t} \geq 0 \\
 S_1 - S_3 &= \delta_1 - \delta_3 - \sum_{t \in S_1} v_{h,t} - \sum_{t \in S_3} v_{h,t} \geq 0 \\
 S_1 &= \delta_1 - N_{S_1} v_w - N_{S_1} v_d - \sum_{t \in S_1} v_{h,t} \geq 0
 \end{aligned}$$

where  $S_j$  are the realized surpluses.  $S_j = \delta_j - N_{S_j} v_w - N_{S_j} v_d - \sum_{t \in S_j} v_{h,t}$ . Define the vector,  $z^t = (S_1 - S_2, S_1 - S_3, S_1)$ .

$$z \sim N(\mu, \Sigma)$$

$$\mu^t = (\delta_1 - \delta_2, \delta_1 - \delta_3, \delta_1)$$

$$\Sigma = \begin{bmatrix} (N_{S_1} + N_{S_2}) \sigma_h^2 & N_{S_1} \sigma_h^2 & N_{S_1} \sigma_h^2 \\ N_{S_1} \sigma_h^2 & (N_{S_1} + N_{S_3}) \sigma_h^2 & N_{S_1} \sigma_h^2 \\ N_{S_1} \sigma_h^2 & N_{S_1} \sigma_h^2 & N_{S_1}^2 \sigma_w^2 + N_{S_1}^2 \sigma_d^2 + N_{S_1} \sigma_h^2 \end{bmatrix}$$

The probability of working shift 1,  $\pi_1$ , is simply the integral of the random vector  $z$  over the positive orthant ( $\mathbb{R}^{3+}$ ).

$$\pi_1 = \int_{\mathbb{R}^{3+}} \phi(z|\mu, \Sigma) dz$$

Here  $\phi()$  is the multivariate normal density. Expected surplus for working shift 1 given shift 1 is worked is the expected value of the last element of the  $z$  vector truncated to the positive orthant.

$$E[S_1|\text{work}] = E[z_3|z \in \mathbb{R}^{3+}] \quad (17)$$

Expected labor supply and expected surplus can simply be calculated by summing over the  $\{\pi_j\}$  and taking the weighted average of the surplus conditional on working given in (17).

We used GHK importance sampling methods based on Halton sequences to compute the truncated normal probabilities using the implementation in the R package, `bayesm`, routine

`ghkvec` (with 1000 long sequences). The moments of truncated multivariate normal random variables can be computed by exploiting recurrence relationships and we used the R package, `tmvtnorm`, implementation.