

## Uber versus Taxi: A Driver’s Eye View<sup>†</sup>

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*Rideshare drivers pay a proportion of their fares to a ride-hailing platform operator, a commission-based compensation model used by many service providers. To Uber drivers, this commission is known as the Uber fee. By contrast, traditional taxi drivers in most US cities make a fixed payment independent of their earnings, usually a weekly or daily medallion lease, keeping every fare dollar net of lease costs and other expenses. We assess these compensation models using an experiment that offered random samples of Boston Uber drivers opportunities to lease a virtual taxi medallion that eliminates the Uber fee. Some drivers were offered a negative fee. Drivers’ labor supply response to our offers reveals a large intertemporal substitution elasticity, on the order of 1.2, and higher for those who accept lease contracts. At the same time, our virtual lease program was undersubscribed: many drivers who would have benefited from buying an inexpensive lease chose to sit out. We use these results to compute the average compensation required to make drivers indifferent between rideshare and taxi-style compensation contracts. The results suggest that rideshare drivers gain considerably from the opportunity to drive without leasing. (JEL J22, J31, L84, L92)*

Other Driver issues [the New York Taxi and Limousine Commission] identified include the perceived inflexibility of leases currently offered by lessors as well as the stress associated with starting shifts “in the red” having paid a set lease price at the beginning of shifts.

—New York Taxi and Limousine Commission Resolution (2015)

**T**raditional taxi drivers in most large American cities must own or lease one of a limited number of medallions granting them the right to drive. Until recently,

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limited supply had turned medallions into valuable assets, typically held by investors or fleet owners and worth hundreds of thousands of dollars. Most big city taxi drivers therefore lease their medallions by the shift, day, or week. Taxi drivers can drive as much or as little as they want, but they are on the hook for the lease. The rise of rideshare platforms, including Uber, means that many workers now have the opportunity to add to their earnings by driving private vehicles, no medallion lease required. By the summer of 2016, Uber had almost 20,000 active drivers in Boston, a figure that can be compared with Boston's long-fixed 1,825 taxi medallions.

In addition to reducing entry barriers and perhaps taxi fares, an important feature of the rideshare model is a proportional compensation scheme, with few fixed costs.<sup>1</sup> In return for a percentage of their earnings known to drivers as a fee or commission, rideshare drivers can set a work schedule without having to worry about covering a lease. Drivers who work long hours are still better off leasing because they keep every dollar earned on a relatively high farebox. But drivers with low hours should prefer to work on a rideshare platform.

This paper uses a series of randomized experiments to compare the value of the proportional compensation scheme offered by rideshare companies with traditional taxi compensation (Angrist, Caldwell, and Hall 2021). The latter can be seen as an exemplar of work arrangements whereby workers buy the firm in the sense that they keep every dollar earned after expenses. Our experiments offered random samples of Boston Uber drivers the opportunity to buy a virtual lease that eliminated or reduced the Uber fee. Some lease-paying drivers were offered a negative fee, capturing a possibly higher taxi wage.

We use drivers' labor supply behavior and lease choices to estimate the parameters that determine the value of a rideshare compensation contract. The first key parameter of interest is the labor supply response to temporarily higher wage rates, or intertemporal substitution elasticity (ISE). A large ISE tends to make medallion-type compensation contracts more attractive because elastic drivers collect additional surplus by driving longer hours when their hourly wage goes up. Drivers' response to experimental wage changes reveals an ISE for the wage effect on Uber hours, on the order of 1.2 overall, and around 1.8 for drivers who lease. These estimates are broadly consistent with experimental estimates reported for Swiss bicycle messengers by Fehr and Goette (2007).<sup>2</sup> Our estimated ISEs are remarkably stable across groups with varying levels of experience and work intensity. They're also broadly in line with the Mas and Pallais (2017) experimental estimates of compensated elasticities for part-time workers who work flexible hours.

The second key parameter in our framework quantifies the extent to which attractive leasing arrangements were undersubscribed. Many drivers to whom we offered a lease indeed took it. But many drivers who would have benefitted from leasing failed to take advantage of the opportunity to do so. We refer to this behavior as "lease aversion" and use a model of context-specific loss aversion to explain it. Specifically, we compute a behavioral lease-aversion coefficient that rationalizes the

<sup>1</sup> Some cities, including New York and (until recently) Houston, impose additional licensure and training costs on ride-hailing drivers.

<sup>2</sup> See Farber (2005, 2015) for more on taxi driver supply elasticities.

lease take-up rates seen in our experiment. This coefficient is also reasonably stable across driver groups. Even without lease aversion, a switch from leasing to proportional compensation generates considerable surplus for most of the drivers in our sample unless lease prices fall below about \$100 per week. In the context of a \$200 weekly lease, lease aversion increases Boston drivers' average rideshare surplus to nearly one-third of their Uber earnings.

A proportional compensation scheme is not the only difference between rideshare and traditional taxi. Prior work has shown that rideshare drivers—especially female and low-income drivers—value the ability to drive flexible shifts, with no minimum shift requirement (Chen et al. 2019, Chen et al. 2020). Some drivers may benefit from wages that quickly respond to supply and demand (“surge” pricing) (Castillo 2019) or they may value driving their own vehicle. Even so, our results isolate worker response to an essential feature of rideshare compensation.

Price theory suggests that lease-type arrangements are more efficient than a proportional fee, since the latter inserts a wedge between effort and income (see, e.g., Lazear and Oyer 2012). Our results show why it may be difficult to implement lease-type schemes in practice. While this paper focuses on the value of proportional fee schemes for rideshare drivers, our results are relevant for any job where the right to work must be purchased at either a flat rate or by giving up a share of earnings. For example, service professionals like hair stylists and cosmetologists face this sort of choice, working on commission or renting a salon chair. Many franchise contracts also reflect this trade-off: potential franchisees often pay a fixed cost to the franchise owner, as well as or instead of a royalty quoted as a percentage of sales.

The next section outlines a theoretical framework that contrasts incentives and constraints under the taxi and rideshare compensation schemes. Section II describes our experimental design and context. Section III presents estimates of drivers' labor supply elasticities. Section IV analyzes the Taxi take-up decision and shows that low take-up is best explained by loss aversion. Section V discusses estimates of compensating variation, comparing rideshare and leasing. Section VI concludes.

## I. Theoretical Framework

Our experiment is motivated by a stylized contrast between the compensation schemes embedded in rideshare and traditional taxi work arrangements. In Boston, until recently, Uber retained a flat fee of 20 percent or 25 percent of its drivers gross fares (referred to here as the “farebox”; these are base fares plus any increase due to Uber's surge multiplier; drivers who started before September 2015 were grandfathered into the lower fee). Most taxi drivers must lease a medallion (the legal right to drive) per shift, day, or week, but can then drive commission-free. Expenses (mostly gas) are paid by drivers under both schemes. Taxi medallion leases may or may not cover use of a vehicle. Uber also offered its drivers the opportunity to rent or lease cars through a program known as “vehicle solutions,” though few drivers did this.<sup>3</sup>

<sup>3</sup>Lyft offers its drivers a similar compensation arrangement. Uber changed its pay policy in June 2017 to loosen the link between rider fares and driver earnings, an innovation known as “upfront pricing.” Lyft has experimented

### A. Budget Sets

We capitalize “Taxi” when referring to the lease-based compensation schemes offered to Uber drivers in our experiment. This is cast against a simplified but realistic characterization of the “Rideshare” contract facing Uber drivers. Fares are cast in terms of average hourly earnings,  $w$ , taken to be the same for Rideshare and Taxi drivers. This is unrestrictive because differences in wages can be modeled as part of the Rideshare fee, or reflected in a negative fee for Taxi drivers.

Drivers drive for  $h$  hours, so their weekly farebox is  $wh$ . Their compensation schemes are as follows:

- Rideshare drivers earn  $y_0 = w(1 - t_0)h$ , where  $t_0$  is the Rideshare fee.
- Taxi drivers earn  $y_1 = w(1 - t_1)h - L$ , where  $L$  is a Taxi lease price and  $t_1 \leq 0$  reflects a possibly higher Taxi wage.

Drivers can choose not to work and earn nothing, but leases must be purchased in advance. The quantity  $t_0 - t_1$  is the difference in tax rates imposed under the two contracts.

Our experiment ran for one week at a time. Many drivers indeed lease weekly, so it is natural to think of  $L$  as a weekly lease, with drivers choosing Rideshare and Taxi week by week. Alternately, we can imagine Taxi as permanently displacing Rideshare or vice versa, in which case the relevant decision-making horizon might be longer, with  $L$  scaled accordingly. After laying out the basic framework, we briefly consider the contrast between Taxi and Rideshare in a life-cycle framework where the opportunity to choose between contracts may be transitory and future wages are uncertain.

Figure 1 sketches the Rideshare and Taxi budget sets when  $w = 20$ ,  $L = 100$ ,  $t_1 = 0$ , and  $t_0 = 0.25$ , so the difference in tax rates in this example is just the Rideshare fee (these are realistic values for wages and fees in Boston, but real-world medallion lease costs are much higher). In general, the budget lines cross where the farebox solves

$$wh = \frac{L}{t_0 - t_1} \equiv B,$$

a quantity we call the Taxi *breakeven*. This is \$400 in the figure, attained by drivers who drive at least 20 hours. Drivers who collect more than \$400 in fares come out ahead under Taxi, while drivers with a lower farebox take home more under Rideshare. Note that the indifference curves sketched in this figure reflect increasing utility as the curves shift northwest. A driver with indifference curve  $u_0$  prefers Rideshare, while a driver with indifference curve  $u_1$  prefers Taxi.

Figure 1 compares a pair of drivers with fareboxes above and below breakeven. Drivers with hours above breakeven clearly benefit from Taxi. But some drivers with a below-breakeven farebox under Rideshare may respond to the higher Taxi wage

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with similar schemes. Neither rideshare platform requires drivers to make advance payments analogous to medallion leasing, though rideshare upstarts such as Fasten have tried such schemes.

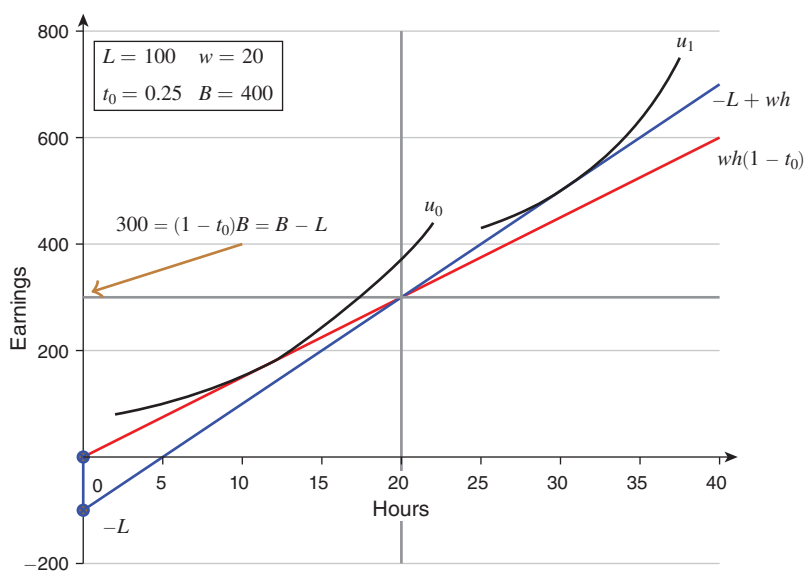


FIGURE 1. RIDESHARE AND TAXI BUDGET LINES

Notes: This figure contrasts the Rideshare and Taxi budget sets. The red line shows the Rideshare budget for a driver who collects \$20 in fares each hour and pays a 25 percent fee. The blue line shows the corresponding Taxi budget set given a lease price of \$100. The two lines cross at the breakeven point with \$300 of after-tax earnings. The two black lines depict indifference curves for a driver who prefers the proportional fee ( $u_0$ ) and for a driver who prefers to lease ( $u_1$ ).

by driving longer hours, thereby clearing breakeven. This scenario is sketched in Figure 2. As in Ashenfelter’s (1983) analysis of welfare program participation, we compute the theoretical take-up threshold by expanding an excess expenditure function that approximates the cash transfer required to attain a reference utility level.

The expenditure function for a generic labor supply problem is

$$e(p, w, \bar{u}) \equiv \min_{x,l} px + wl \quad \text{subject to} \quad u(x, l) = \bar{u},$$

giving the minimum spent on consumption ( $x$ ) at price  $p$  and leisure ( $l$ ) at price  $w$  in the effort to reach utility  $\bar{u}$ . Excess expenditure is spending minus the value of drivers’ time endowment,  $T$ , that is,

$$s(w, \bar{u}) \equiv e(p, w, \bar{u}) - wT.$$

Using the fact that expenditure is minimized by compensated demand functions,  $x^c$  and  $l^c$ , we can write

$$s(w, \bar{u}) = px^c + wl^c - wT = px^c - wh^c.$$

The cash needed to reach a given utility level is the difference between consumption spending and driver earnings when these quantities are chosen optimally.

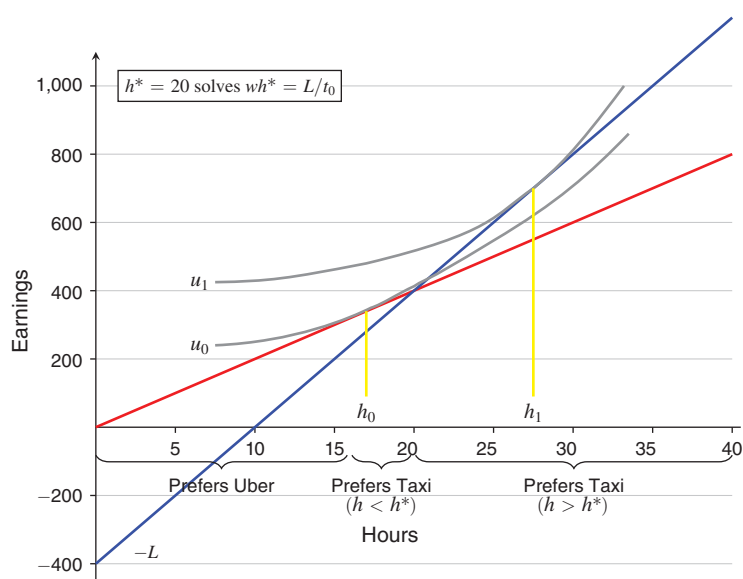


FIGURE 2. DRIVEN AND ELASTIC DRIVERS TAKE TAXI

Notes: This figure sketches choices made by two types of drivers, those whose Rideshare hours are such that they would earn more by leasing, and those who earn less ex ante but are elastic enough to find leasing attractive anyway. Indifference curves  $u_0$  and  $u_1$  belong to a driver in the second group. While her Rideshare hours  $h_0$  are not sufficient to pay off the lease, she increases her hours worked to  $h_1$  when offered Taxi.

We model Rideshare and Taxi in this framework by treating lease costs and ride-hailing fees as parameters in an expanded excess expenditure function. Ignoring other earnings opportunities for the moment, the cash transfer needed to attain  $\bar{u}$  when driving under a scheme with  $L$  and  $t$  as parameters can be written

$$f(w, \bar{u}; t, L) = (px^c + L) - w(1 - t)h^c = s(w[1 - t], \bar{u}) + L.$$

Let  $u_0$  denote utility attained when driving Rideshare, a contract described by  $L = 0$ ,  $t = t_0$ . Drivers prefer Taxi when the Taxi contract allows them to reach  $u_0$  for less than  $f(w, u_0; t_0, 0)$ . Specifically, assuming  $t_1 = 0$ , Uber drivers take Taxi when

$$\underbrace{f(w, u_0; 0, L)}_{\text{Taxi}} < \underbrace{f(w, u_0; t_0, 0)}_{\text{Rideshare}},$$

or, equivalently, when

$$(1) \quad s(w, u_0) + L < s(w_0, u_0),$$

where  $w_0 = w(1 - t_0)$  is the after-fee Uber wage. Taking a second-order expansion of  $s(w, u_0)$  around  $s(w_0, u_0)$  and simplifying using Shephard's lemma, the Taxi participation rule is

$$(2) \quad L - t_0 w h_0 - \frac{1}{2} \left( \frac{\partial h^c}{\partial w} \frac{w(1 - t_0)}{h_0} \right) t_0 w h_0 \frac{t_0}{1 - t_0} < 0,$$

where  $h_0$  is Rideshare labor supply.<sup>4</sup>

It is useful to rewrite the Taxi participation rule in terms of the Taxi breakeven,

$$(3) \quad \underbrace{wh_0}_{\text{Rideshare farebox}} > \underbrace{\frac{L}{t_0} \left(1 + \frac{\delta}{2} \frac{t_0}{1-t_0}\right)^{-1}}_{\text{adjusted breakeven}},$$

where  $\delta$  is the substitution elasticity evaluated at the after-fee Rideshare wage,

$$\delta \equiv \frac{\partial h^c}{\partial w} \frac{w(1-t_0)}{h_0} = \frac{\partial h^c}{\partial w} \frac{w_0}{h_0}$$

and  $w_0 = (1-t_0)w$ . This shows that a positive substitution elasticity reduces the participation threshold by the proportional amount

$$\frac{1}{1 + 0.5\delta \frac{t_0}{1-t_0}}.$$

Eligible drivers with a Rideshare farebox that clears breakeven should always prefer Taxi. But some with a farebox below breakeven should also accept a Taxi contract. With a unit-elastic compensated response and a fee of 25 percent, for example, we expect the participation threshold to be reduced relative to breakeven by about 14.5 percent.

### B. *Compensating for Taxi-Type Compensation*

To model driver choices between work arrangements, we derive the payment required to make up for loss of the opportunity to drive under a proportional fee-based contract. This is compensating variation (CV), where the baseline condition is the Rideshare budget line with an interior solution and the alternative is the Taxi budget set. Positive CV means payment is required for imposition of Taxi, while negative values arise for drivers who prefer Taxi. Although CV is tied to the specifics of the compensation scheme on offer, the results of our experimental Taxi-Rideshare comparisons can be used to extrapolate compensation values to other markets where workers might choose between paying a proportional tax on their earnings and paying a fixed up-front fee.

Formally, CV is the difference in cash required to reach a reference utility level given the Taxi and Rideshare budget lines:

$$f(w, u_0; 0, L) - f(w, u_0; t_0, 0),$$

where  $u_0$  is the Rideshare utility level. Using Shephard's lemma as in equation (2), the CV required as compensation for Taxi can be shown to be

$$(4) \quad CV = \{L - t_0 w h_0\} - t_0 w h_0 \frac{\delta t_0}{2(1-t_0)}.$$

<sup>4</sup>We omit the superscript indicating that this is the level of work determined by the compensated supply function.



Rideshare drivers for whom CV is negative take the Taxi scheme when offered, producing the participation rule described by (2).

A Leontief ( $\delta = 0$ ) driver should be paid the difference between his or her lease costs and Rideshare fees. Elastic labor supply favors Taxi, reducing CV. Even so, the principal determinant of CV for most drivers is likely to be  $L - t_0 w h_0$ , the difference between lease costs and Rideshare fees. This difference is largest for Uber and Lyft's many low-hours drivers. Recall also that in the absence of substantial income effects on the demand for leisure, CV approximates the difference in driver surplus yielded by the two compensation schemes (this in turn equals the corresponding equivalent variation).

The left panel of Figure 3 illustrates the CV calculation generated by a move from the Rideshare to Taxi budget lines. A Rideshare driver working at point A drives 10 hours and is on indifference curve  $u_0$ . Faced with a Taxi budget line, this driver drives 13 hours, but is worse off on  $u_1$ . It seems natural to compensate this driver by an amount equal to the excess of his lease over what he used to pay in Rideshare fees. But a payment of  $L - t_0 w h_0$  puts non-Leontief drivers above point C on  $u_0$ , as indicated by the blue line extending from point A with a slope equal to the Taxi wage. Payments equal to lease costs minus ex ante Rideshare fees overcompensate for Taxi because the Taxi scheme increases wages, yielding additional driver surplus. The term  $w h_0 (\delta t_0 / (2(1 - t_0)))$  in equation (4) captures this surplus, a term denoted by  $\sigma$  in Figure 3. The surplus generated by higher Taxi wages is the product of the proportional Taxi wage advantage,  $t_0 / (1 - t_0)$ , the substitution elasticity ( $\delta$ ), and driver fees,  $t_0 w h_0$ . This product approximates the area under the driver's supply curve between his net-of-fee Rideshare and Taxi wages.

*Choosing Not to Drive.*—The compensation formula above presumes Rideshare drivers accept the Taxi budget line as a condition for compensation. But we might instead allow former Rideshare drivers to refuse Taxi, taking some of their compensation in the form of increased leisure. In this scenario, drivers are made whole by imagined unemployment insurance (UI) in an amount that takes them to the  $u_0$  ordinate, a scenario illustrated in the right panel of Figure 3.

To compute the compensation needed in this case, we assume the marginal utility of leisure is zero at  $h = 0$ , so drivers with a wage of zero drive zero hours. Expanding the excess expenditure function for Rideshare utility with a wage of zero around Rideshare expenditure with a fee of  $t_0$ , we have

$$(5) \quad s(0, u_0) = s(w_0, u_0) + (-h_0)(-w(1 - t_0)) - \frac{1}{2} \frac{\partial h^c}{\partial w} w^2 (1 - t_0)^2.$$

By definition of  $u_0$ , Rideshare drivers with no unearned income and no lease to cover have consumption equal to their Rideshare earnings, so  $s(w_0, u_0) = 0$ . The compensation required for the replacement of Rideshare work opportunities with UI is therefore

$$(6) \quad UI = (1 - t_0) w h_0 - \frac{1}{2} \left( \frac{\partial h^c}{\partial w} \frac{w(1 - t_0)}{h_0} \right) ([1 - t_0] w h_0)$$

$$(7) \quad = (1 - t_0) w h_0 \left[ 1 - \frac{\delta}{2} \right].$$



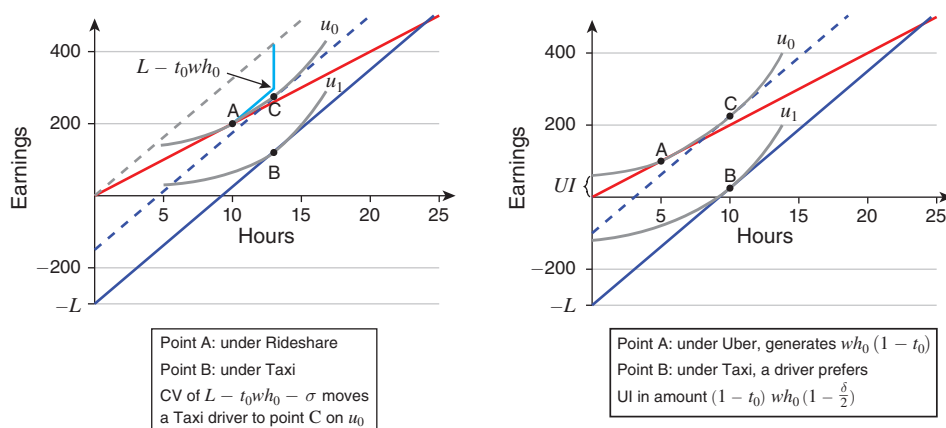


FIGURE 3. RIDESHARE VERSUS TAXI COMPENSATING VARIATION

Notes: The figure on the left shows how to compute compensating variation for a driver who moves from Rideshare to Taxi. Indifference curve  $u_0$  is tangent to the Rideshare budget set at point A, where this Rideshare driver works 10 hours/week and earns \$200/week. A Taxi contract without compensation moves this driver to point B. Point C indicates the point on  $u_0$  with the same slope as the Taxi budget set. CV for Taxi is given by the distance from B to C, and falls below lease costs net of ex ante fees. The dashed grey line is parallel to the blue line, shifted up by the lease amount,  $L$ . The arrow shows the utility level associated with working  $h_1$  if the driver is compensated by the naive amount: the full cost of the lease, less the reduction in fees, calculated using Rideshare hours. The fact that this is above point C—the point along the original indifference curve associated with  $h_1$ —illustrates that this naive compensation level is too high. In order to compensate the driver and move her to point C, the driver must be given  $L - t_0wh_0 - \sigma$ , where  $\sigma$  adjusts for driver surplus due to higher wages. The figure on the right shows how this calculation is modified if the driver has access to unemployment compensation of the sort described in Section IB.

The replacement rate for lost Rideshare earnings in this case is approximately one minus half the compensated labor supply elasticity. For Leontief drivers, the replacement rate is 100 percent since their  $\delta = 0$ .

### C. Life Cycle Considerations

We compare Rideshare and Taxi in a multiperiod setting using the Browning, Deaton, and Irish (1985) duality framework built around the profit function. Just as the excess expenditure function is the potential function for compensated labor supply at a fixed utility level, the profit function is the potential function for Frisch labor supply. These supply functions characterize the response to perfectly anticipated wage changes (MaCurdy 1981 calls these “evolutionary” wage changes) or to transitory changes that have little effect on lifetime wealth (more precisely, little effect on the marginal utility of lifetime wealth). The derivative of Frisch labor supply with respect to the wage rate is the Frisch elasticity or ISE.

With intertemporally additive preferences and a known path for wages, workers’ total profit functions are given by the sum of period- $s$  profit functions,  $\pi_s(r, w_s, p_s)$ , defined as

$$\pi_s(r, w_s, p_s) \equiv \max_{u, x, l} ru + w_s(T - l) - p_s x; \quad u = v_s(x, l),$$

where  $r$  is the reciprocal of the marginal utility of wealth,  $v_s(x, l)$  is period- $s$  utility, and wages and prices in period  $s$  are time-varying. The profit function imagines consumers valuing their utility at price  $r$ ; profit is then the monetary value of utility plus earnings, net of expenditure on inputs in the form of consumption.

Consider a driver making a life-cycle plan in the face of known wages and prices, choosing between Rideshare and Taxi at time (week)  $s$ . This driver prefers Taxi if the Taxi contract is profitable for that week. That is, Taxi beats Rideshare in week  $s$  when

$$\pi_s(r, w_s) - \pi_s(r, w_s[1 - t_0]) > L.$$

This comparison presumes the utility price is unchanged by Taxi, either because the Taxi opportunity and parameters are known at the time plans are made, or because the Taxi option is short-lived. We assume goods prices are constant, so  $p_s$  is left in the background.<sup>5</sup>

Expanding  $\pi_s(r, w_s)$  around the value of Rideshare profits,  $\pi_s(r, w_s[1 - t_0])$ , the life-cycle participation rule for Taxi at week  $s$  is approximated by

$$(8) \quad \frac{\partial \pi_s(r, w_s[1 - t_0])}{\partial w} w_s t_0 + \frac{1}{2} \frac{\partial^2 \pi_s(r, w_s[1 - t_0])}{\partial w^2} (w_s t_0)^2 > L.$$

Applying a life-cycle version of Shephard's lemma, this can be written

$$(9) \quad \underbrace{w_s h_{s0}}_{\text{Rideshare earnings}} > \underbrace{\frac{L}{t_0} \left( 1 + \frac{\delta^f t_0}{2(1 - t_0)} \right)^{-1}}_{\text{life-cycle breakeven}},$$

where  $\delta^f \equiv (\partial h_s^f(r, w_s) / \partial w_s)(w_s(1 - t_0)/h)$  and  $h_{s0} \equiv h_s^f(r, w_s[1 - t_0])$  is Frisch labor supply for Rideshare drivers in period  $s$ . The earlier Taxi participation rule therefore stands—but with the Hicks substitution elasticity replaced by the possibly larger ISE,  $\delta^f$ .

The revision to CV in a life-cycle framework parallels that for participation. Specifically, CV is the sum of the difference in within-period profits under the two compensation schemes:

$$CV = [\pi_s(r, w_s) - L] - \pi_s(r, w_s[1 - t_0]).$$

Using the expansion yielding equation (8), this becomes

$$(10) \quad CV = \{L - t_0 w_s h_{s0}\} - t_0 w_s h_{s0} \frac{\delta^f t_0}{2(1 - t_0)}.$$

This is the same as (4), with the ISE  $\delta^f$  again replacing the substitution elasticity,  $\delta$ . Since the ISE (weakly) exceeds the Hicks substitution elasticity, a life-cycle

<sup>5</sup>Our streamlined notation also ignores the fact that wage and price variables determining profits in a future period  $s$  are discounted back to the decision-making date; see Browning, Deaton, and Irish (1985) for details.

perspective tends to favor Taxi. Because our experimental design offers temporary wage changes, we interpret the experiment as identifying  $\delta^f$ .

In practice, drivers considering a weekly lease must do so without knowing next week's wage or farebox. Suppose that a Rideshare driver who doesn't know next week's wages is offered the opportunity to buy a one-week lease. Although marginal utility of lifetime wealth presumably changes little as a result of wage surprises, some idea of  $w$  is required to make a wise near-term choice. Assuming drivers know how they will respond to wages, a predicted wage implies a predicted farebox. The econometric framework outlined in Section IV therefore embeds farebox prediction in an empirical model for Taxi participation.

#### D. Outside Options

The drivers in our experiment can typically drive as many hours for Uber as they like at the implicit market wage, but many Rideshare drivers work at another job (Hall and Krueger 2018). We model alternative employment as characterized by declining earnings opportunities. For alternative jobs with institutional limits on hours, such as shift work or salaried office work, the decline is likely to be precipitous. On other sorts of jobs, including alternative ride-hailing platforms, any pay advantage over Uber may taper smoothly. We might imagine, for example, that Lyft takes lower fees than Uber, but offers its drivers less steady trip demand. This market structure is captured by assuming that drivers earn  $e(a)$  for  $a$  hours worked on an alternative job, where  $e(a)$  is increasing but concave.<sup>6</sup>

The excess expenditure function for a driver who holds an alternative job is

$$s^a(p, w, \bar{u}) = \min_{x, h, d} px - wh - e(a) \quad \text{subject to} \quad u(x, T - h - a) = \bar{u},$$

where the  $a$  superscript indicates that this is excess expenditure for someone who works an alternative job. As always, excess expenditure is minimized by the compensated demand functions  $x^c, h^c, a^c$ , so

$$s^a(p, w, \bar{u}) = px^c - wh^c - e(a^c).$$

Writing  $f^a(w, \bar{u}, L, t)$  for the cash required to reach utility  $\bar{u}$  in this scenario yields the relevant excess expenditure functions:

- Rideshare:  $f^a(w, \bar{u}; t_0, 0) = px^c - w(1 - t)h^c - e(a^c)$   
 $= s^a(w(1 - t_0), \bar{u}) = s^a(w_0, \bar{u});$
- Taxi:  $f^a(w, \bar{u}; 0, L) = (px^c + L) - wh^c - e(a^c) = s^a(w, \bar{u}) + L,$

<sup>6</sup>This setup is inspired by the Gronau (1977) model of home production, where workers get utility from a single consumption good and from leisure, and can produce the consumption good under diminishing returns at home or buy it with money earned on a job paying constant wages.

where it is understood that compensated demand functions are different in the two schemes. The online Appendix derives the usual Shephard's lemma result in this context:

$$(11) \quad \frac{\partial f^a}{\partial w} = \frac{\partial s^a}{\partial w} = -h^c,$$

with the modification that compensated labor supply now includes only hours worked as a driver.

We can again use Shephard's lemma to show that Rideshare drivers with alternative jobs are happy to drive Taxi when

$$(12) \quad wh_0 > \frac{L}{t_0} \left( 1 + \frac{1}{2(1-t_0)} \tilde{\delta} t_0 \right)^{-1}.$$

This looks like (3), but the substitution elasticity in this case, denoted by  $\tilde{\delta}$ , measures the change in *hours driving for Uber*, while total labor supply includes hours driving plus hours worked on the alternative job,  $H = h + a$ . The formula for CV is adjusted similarly. The wage elasticity of hours driving for a particular platform is likely to be larger than the elasticity of total hours worked since changes in  $H$  may reflect substitution from  $h$  to  $a$  with little change in  $H$ . Because our experiment measures the change in hours driving for Uber, this change in the interpretation of parameters leaves our welfare analysis unchanged.

## II. Experimental Design

Uber and its ride-hailing competitors routinely offer drivers temporary increases in pay (known as “promotions”) that are designed to boost the supply of trips. We estimate labor supply elasticities and lease aversion parameters using a randomized experiment presented to drivers as an Uber promotion called the *Earnings Accelerator*.

### A. Overview

The experiment unfolded in three phases: (i) selection of eligible drivers, (ii) opt-in treatment weeks, and (iii) Taxi treatment weeks. The opt-in phase was designed to select drivers who seem likely to take note of Uber's promotional messaging and to obtain drivers' consent to receive Taxi offers. Initial ISE estimates from the opt-in phase also allowed us to calibrate lease prices. Finally, the Taxi phase identified drivers' willingness to lease and provided further evidence on intertemporal substitution. Online Appendix Table A1 sketches the experimental timeline.

Drivers were eligible for inclusion in the experiment if they took at least four trips and drove an average of 5–25 hours per week in the four weeks prior to selection of the experimental sample (the last three weeks of July and the first week of August 2016). The omission of high-hours drivers—those with average weekly hours above 25—reduced experimental costs and allowed us to focus on a sample of drivers with farebox values clustered around modest Taxi breakevens. High-hours drivers may

TABLE 1—BOSTON UBER DRIVERS

	All Boston drivers (1)	Eligible drivers (2)	Experimental drivers (3)	Strata-adjusted difference (4)
Female	0.14 (0.35)	0.14 (0.34)	0.14 (0.35)	0.00 (0.01)
Age	40.90 (12.13)	41.58 (12.20)	41.80 (12.29)	0.15 (0.36)
Average hours/week in the month before selection	14.42 (14.39)	13.13 (5.69)	14.51 (5.81)	0.06 (0.08)
Average hourly earnings in the month before selection	15.39 (8.64)	17.59 (6.19)	17.40 (6.05)	−0.10 (0.17)
Average weekly Farebox in the month before selection	372.06 (447.51)	310.91 (192.04)	342.82 (198.12)	−0.80 (3.93)
Months since sign-up	13.89 (9.43)	14.26 (9.25)	11.14 (8.67)	−0.08 (0.15)
Vehicle solutions participant	0.08 (0.26)	0.08 (0.27)	0.08 (0.28)	0.01 (0.01)
Car model year 2003 or older	0.03 (0.17)	0.03 (0.17)	0.12 (0.33)	--- ---
Car model year 2011 or newer	0.64 (0.48)	0.64 (0.48)	0.56 (0.50)	−0.01 (0.01)
Commission	22.34 (2.50)	22.24 (2.49)	23.21 (2.40)	0.00 (0.01)
Observations	19,316	8,685	1,600	8,685

Notes: Columns 1–2 compare Boston drivers to the subset of drivers eligible for the experiment. Eligible drivers are those with valid vehicle year information who made at least 4 trips during the past 30 days and drove an average of between 5 and 25 hours/week in July 2016. Column 3 shows means for drivers in the experimental sample. Treatment was randomly assigned within strata defined by hours (high/low), commission (20/25 percent commission), and car age (older/newer than 2003). Column 4 shows strata-adjusted differences between the experimental sample and the rest of the eligible pool. Average hourly earnings include surge pay but are net of Uber fees. Vehicle solutions drivers lease a car through an Uber-sponsored leasing program.

differ from other drivers, but an analysis of drivers grouped by hours driven shows little systematic variation in the behavioral parameters of interest to us.

Roughly 45 percent of Boston drivers were eligible for inclusion in the experiment. Although the cap on hours per week reduces average hours in the eligible sample relative to the city average, drivers in the eligible sample are otherwise similar to the pool of active Boston drivers (that is, the group who took at least four trips in the previous month). For example, 14 percent of both the active and eligible samples are female and both groups had used the Uber platform for an average of 14 months. These comparisons appears in the first two columns of Table 1.

A total of 1,600 eligible drivers were selected for inclusion in the experiment. The experimental design randomized compensation schemes within strata defined by average hours driven in July 2016, driver fee class (commission rate), and vehicle model year. The low-hours stratum includes drivers who averaged 5–15 hours per week, while the high-hours group averaged 15–25 hours per week. The 20 percent fee class includes veteran drivers who signed up before September 2015, while other drivers paid a commission rate of 25 percent. Because Lyft requires its drivers to use cars no older than 2004, our strata distinguish between drivers with cars from model year 2003 or older and drivers with newer Lyft-eligible cars. Table 1 also shows

the proportion of drivers with cars newer than 2010, since Lyft's most important promotion requires drivers operate newer vehicles. Drivers were randomly sampled and randomly assigned to the first or second opt-in week within these three strata. As can be seen in column 4 of Table 1, which reports strata-adjusted differences in means, the experimental sample has characteristics similar to those of drivers in the rest of the eligible sample.

### B. Opt-In Weeks

The 1,600 drivers in the experimental sample were offered the opportunity to drive for one opt-in week with no Uber fee. Half of the drivers (Wave 1) were offered fee-free driving in the first opt-in week. While the first wave was driving fee free, drivers in the second half sample (Wave 2) were offered the chance to opt in to fee-free driving the following week. This split-sample design was meant to balance wealth effects induced by the higher fee-free wage. Online Appendix Table A2 shows that driver characteristics are similar in the two waves.

Drivers in both waves were offered fee-free driving by email, text message, and in-app notification on Monday morning of the relevant offer week; they had until midnight the following Saturday to opt-in. Sampled drivers received up to three emailed reminders to opt-in by the deadline. Drivers who opted in paid no Uber fee on all trips taken in the subsequent week. This was reflected in their immediate in-app trip receipts and weekly pay statements (participating drivers saw a fee of zero in receipts and statements). Fee-free driving increased a driver's total payout by 25 percent in the 20 percent fee class ( $0.25 = (1/0.8) - 1$ ) and by 33 percent in the 25 percent fee class ( $0.33 = (1/0.75) - 1$ ).

Take-up rates for fee-free driving are shown in Table 2. Roughly 64 percent (1,031/1,600) accepted the fee-free offer. Although fee-free driving should be attractive to all drivers, many appear to ignore Uber messaging beyond the offer of trips. This likely reflects the fact that (during our experimental period) Uber drivers received many electronic messages each week.<sup>7</sup> The struggle for driver attention is reflected in a decline in take-up from Wave 1 (71 percent) to Wave 2 (58 percent), after we stopped the opt-in reminders midweek. Messaging was reduced in view of higher-than-expected take-up and a consequent risk of running over budget. Discussions with Uber's Boston team suggest our take-up rates compare favorably with take-up rates for other no-lose driver promotions requiring an opt in. Incomplete take-up may also reflect the fact that drivers who opted in consented for their data to be used in academic research and to receive further Earnings Accelerator offers.

Table 3 shows that drivers who opted in drove and earned more than other drivers during the period preceding opt-in weeks. In the pooled sample including both high and low hours drivers, those who opted in had a pre-experimental farebox roughly \$51 higher than the farebox of drivers who opted out. Those who opted in also drove four more hours that week. On the other hand, these gaps are much smaller when averaged over the month of July. This is consistent with the idea that inattention drove

<sup>7</sup>In view of this, Uber moved later to cap the number of promotion-related messages sent to drivers.

TABLE 2—EARNINGS ACCELERATOR OPT-IN WEEK DESIGN AND TAKE-UP

Hours Group (1)	Strata		Offers		Opt-ins	
	Car (2)	Uber fee (percent) (3)	Number (4)	Rate (percent) (5)	Number (6)	Rate (percent) (7)
Wave 1						
High hours	New	20	102	6	75	74
	New	25	202	17	155	77
	Old	—	96	100	61	64
		—	400	13	291	73
Low hours	New	20	100	4	68	68
	New	25	200	8	148	74
	Old	—	100	54	64	64
	—	—	400	7	280	70
Total			800		571	
Wave 2						
High hours	New	20	150	8	84	56
	New	25	250	21	154	62
		—	400	13	238	60
Low hours	New	20	250	9	133	53
	New	25	150	6	89	59
	—	—	400	7	222	56
Total			800		460	

*Notes:* This table describes the offer distribution and take-up rates in the initial pair of opt-in weeks, designated Wave 1 and Wave 2. This phase of the experiment randomly assigned offers within strata defined by columns 1–3: hours group, car model year, and (pre-experimental) Uber fee. Column 4 shows the number of offers that were made in each stratum. Column 5 shows the percent of eligible Boston drivers offered fee-free driving. Column 6 reports the number of drivers who accepted an offer and column 7 reports offer acceptance rate. The last row for each hours group reports totals for that week and hours group; the last row for each wave shows the overall total for that week.

low opt-in rates: drivers who drove during the week we sent treatment offers had more chances to learn of the Earnings Accelerator promotion through an in-app notification. In addition to driving more hours, participating drivers were a little younger. Other characteristics, including average commission rates, percent female, and months on platform, differ little by participation status.

### C. Taxi Treatments

The Taxi phase of the experiment offered randomly chosen subsets of the 1,031 drivers who opted in to fee-free driving the opportunity to buy additional weeks of fee-free driving for a modest lease. These Taxi treatments were randomly assigned within strata defined by average hours and fee. Eight treatments were offered in each Taxi week, two for each hours/fee combination. Online Appendix Tables A3 and A4 show that random assignment balanced the characteristics of drivers in the Taxi treatment and control groups.

Each Taxi treatment consists of a fee reduction,  $t_1 - t_0$ , and a lease price,  $L$ . Based on the ISE estimates computed using data from opt-in weeks, lease prices were calibrated so as to be attractive to roughly 60 percent of drivers in each stratum. These lease prices and fee changes are listed in Table 4. In the first Taxi week, 40 percent of drivers in each stratum were offered the opportunity to buy another week of



TABLE 3—WHO OPTS IN?

	Pooled		High hours		Low hours	
	Opt-out mean (1)	Difference (2)	Opt-out mean (3)	Difference (4)	Opt-out mean (5)	Difference (6)
Female	0.13 [0.33]	0.03 (0.02)	0.12 [0.32]	0.01 (0.02)	0.14 [0.35]	0.05 (0.03)
Age	42.75 [12.61]	-1.46 (0.65)	44.81 [12.68]	-3.06 (0.95)	40.89 [12.27]	-0.08 (0.89)
Commission	23.11 [2.43]	0.16 (0.13)	22.97 [2.46]	0.33 (0.18)	23.24 [2.39]	0.00 (0.17)
Vehicle solutions	0.06 [0.24]	0.03 (0.01)	0.07 [0.26]	0.04 (0.02)	0.05 [0.23]	0.02 (0.02)
Vehicle year	2010.40 [4.45]	-1.76 (1.96)	2010.56 [4.39]	-3.50 (3.82)	2010.26 [4.51]	0.06 (0.33)
Months since signup	11.60 [9.03]	-0.71 (0.46)	12.53 [9.19]	-1.61 (0.67)	10.75 [8.81]	0.09 (0.63)
Average hours/week the month before selection	14.16 [6.01]	0.53 (0.31)	19.67 [3.01]	-0.18 (0.22)	9.16 [2.84]	0.49 (0.21)
Average hourly earnings the month before selection	16.19 [5.56]	1.88 (0.30)	17.46 [4.80]	2.30 (0.38)	15.03 [5.95]	1.26 (0.45)
Average weekly Farebox the month before selection	310.06 [180.52]	50.85 (9.90)	447.65 [145.18]	57.13 (11.48)	184.93 [100.90]	24.36 (7.54)
Observations	569	1,600	271	800	298	800

Notes: This table compares the characteristics of drivers who opted in to fee-free driving with those of drivers who were offered fee-free driving but did not participate. Standard deviations appear in brackets. Columns 2, 4, and 6 report the strata-adjusted difference between drivers who opted in and drivers who did not opt in. Standard errors are in parentheses. Average hourly earnings include surge pay but are net of the Uber fee.

fee-free driving and 20 percent were offered negative fee driving in the form of a 12.5 percent wage increase ( $t_1 = -0.125$ ). Lease prices in the first Taxi week ranged from \$45 to \$165. The treatments in week 2 were less generous—the negative fee treatment was replaced with a half-fee treatment—but also less expensive, with leases priced between \$15 and \$60. Each treatment during week 2 was offered to 30 percent of drivers within strata. Figure 4 summarizes experimental staging and design parameters.

As with solicitation for fee-free driving in opt-in week, treated Taxi drivers were offered Taxi contracts via email, text messages, and in-app notifications. These offers were sent one week in advance and highlighted the breakeven amount. For example, drivers in the 25 percent fee class who were offered a half-fee treatment for \$35 were told, “As long as your weekly total fares + surge exceed \$280, you’ll come out ahead.” Email and text messages included links to a simple table contrasting the former and revised fee calculation for a sample trip. Emails and text messages also included links to a calculator that showed net earnings with and without treatment for any driver-selected value of fares plus surge pay. Figure A1 in the online Appendix shows a message delivered in the Taxi promotions; online Appendix Figure A2 shows the calculator.

Drivers who opted-in to Taxi’s virtual lease had lease payments deducted from their pay for the opt-in week. This deduction appeared as a negative entry on

TABLE 4—EARNINGS ACCELERATOR TAXI PARAMETERS AND TAKE-UP

Strata		Treatment				Offers and Opt Ins	
Hours Group	Fee	Number in group	Lease	New fee	Breakeven	Offer rate	Opt-in rate
(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Week 1							
High	0.20	180	\$110	0	\$550	0.4	0.42
			\$165	-0.125	\$508	0.2	0.53
High	0.25	349	\$110	0	\$440	0.4	0.28
			\$165	-0.125	\$440	0.2	0.33
Low	0.2	177	\$45	0	\$225	0.4	0.58
			\$75	-0.125	\$231	0.2	0.51
Low	0.25	325	\$45	0	\$180	0.4	0.48
			\$75	-0.125	\$200	0.2	0.34
Week 2							
High	0.20	180	\$60	0	\$300	0.3	0.50
			\$25	0.10	\$250	0.3	0.46
High	0.25	349	\$55	0	\$220	0.3	0.41
			\$35	0.125	\$280	0.3	0.54
Low	0.2	177	\$40	0	\$200	0.3	0.43
			\$15	0.10	\$150	0.3	0.58
Low	0.25	324	\$35	0	\$140	0.3	0.43
			\$15	0.125	\$120	0.3	0.58

Notes: This table describes the Taxi phase of the experiment in which drivers could purchase a virtual lease giving them a week of fee-free driving. During each of two Taxi weeks, drivers within each stratum (listed in columns 1–3) were randomly assigned to one of two lease treatments (60 percent) or to the control group (40 percent). Columns 4 and 5 describe these treatments. Column 6 reports the breakeven associated with each treatment. Opt-in rates in column 8 are reported as a proportion of drivers offered. Lease prices were chosen so as to be attractive to roughly 60 percent of the drivers in each stratum.

otherwise standard weekly pay statements on the line that typically would show payments earned through Uber promotions.<sup>8</sup> These deductions were labeled “Earnings Accelerator buy-in.” During opt-in week, participating drivers’ trip receipts reflected the reduced fee (see Figure 5 for sample trip receipts and Figure 6 for a participating driver’s weekly pay statement).

Earnings Accelerator lease amounts are well below the price of a traditional taxi medallion lease: before the advent of ride-hailing, Boston medallion leases (including vehicle) ran around \$700/week and over \$100/day. Our virtual medallions were priced from \$50–\$165/week. These amounts were calibrated to appeal to drivers with weekly earnings in particular ranges, as explained below. As a measure of the empirical relevance of our design, it is noteworthy that in 2016 a Boston ride-hailing upstart (Fasten) offered its drivers the option to pay \$80/week or \$15/day to drive fee free.<sup>9</sup>

<sup>8</sup> A few drivers who earned less than needed to cover their lease carried a negative balance into the following pay period.

<sup>9</sup> In 2010, the Boston medallion lease cost for a single driver was capped at \$700/week, \$139/day, and \$77/12-hour shift (BPD Circular Date 12-30-09 “2010 Standard Shift Rental Agreement”). Newer cars leased for an additional \$170/week. Drivers could split a weekly lease for no more than \$800. Before the advent of ride-hailing, short supply meant medallions typically leased at the cap. Side payments to Boston fleet owners also appear to have been common (See the 2013 *Boston Globe* stories linked under <http://www.bostonglobe.com/metro/specials/taxi>). Data on medallion prices is spotty; a *Commonwealth Magazine* article (<http://commonwealthmagazine.org/transportation/taxi-medallion-owners-under-water-and-drowning/>)

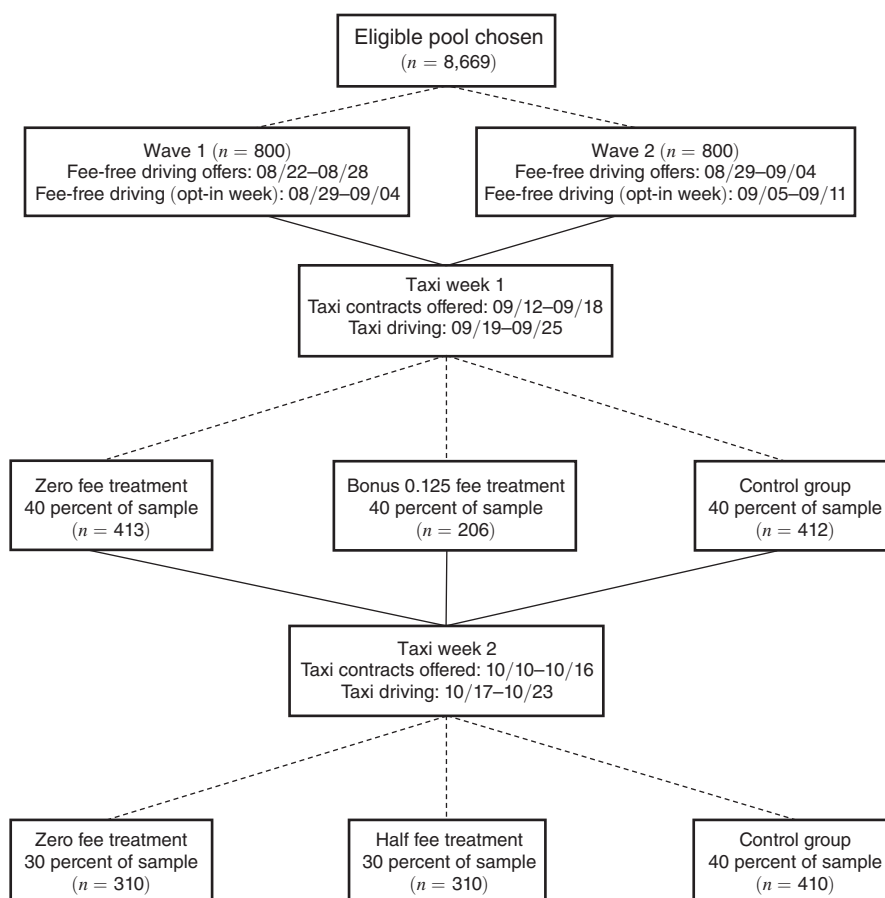


FIGURE 4. EARNINGS ACCELERATOR EXPERIMENTAL DESIGN

Notes: This figure sketches the sequencing and sample sizes associated with each phase of the Earnings Accelerator experiment. Dashed lines denote groupings determined by random assignment.

### III. Labor Supply Effects

#### A. Impacts on Participants

Our labor supply analysis begins with a set of results using offers as instrumental variables in a two-stage least squares (2SLS) setup that captures the impact of Earnings Accelerator *participation* on measures of labor supply. Experimental participation is defined in two ways. First, using the full research sample of 1,600, participants are drivers who agreed to fee-free driving during the opt-in phase. Second, for the 1,031 drivers who opted in, participants are those who purchased

quotes a pre-ride-hailing Boston medallion price of over \$700,000, down more recently to about half of that. NYC medallion prices are said to have peaked at over one million dollars (<http://seekingalpha.com/article/3177766-taxi-farebox-declines-a-harder-hit-to-medallion-owner-bottom-lines?page=2>).

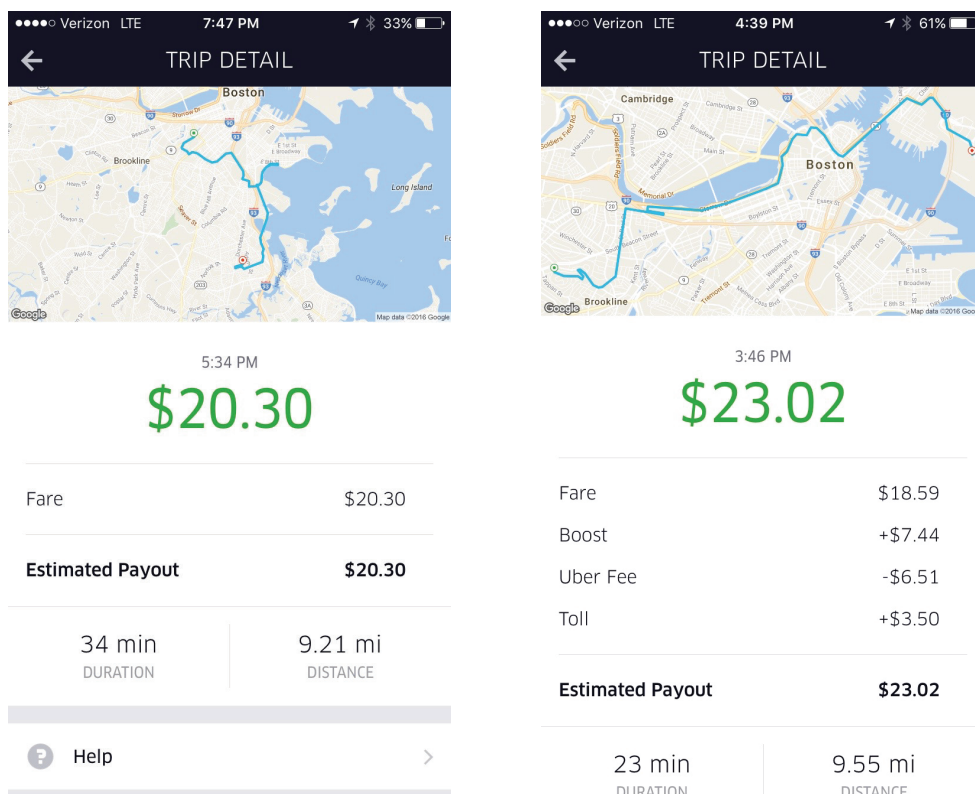


FIGURE 5. EARNINGS ACCELERATOR TRIP RECEIPTS

Notes: This figure shows two trip receipts. The left is for a trip taken while the Earnings Accelerator was active; this driver paid no fee. The right is for a trip taken when the Earnings Accelerator was inactive; this driver paid an Uber fee. The right shows how additional Uber promotions (in this case, Boost) are reflected on trip receipts.

a Taxi contract. Participation estimates distinguish extensive from intensive margin effects, identify possible changes in average hourly compensation, and reveal anticipatory or post-treatment labor supply changes that might signal confounding wealth effects. The participation analysis yields three important findings: (i) Earnings Accelerator participation had no effect on the extensive margin (that is, effects on whether drivers drive at all); (ii) participation boosted hours driven and driver earnings considerably during treatment weeks, with no corresponding change in average hourly earnings; (iii) we see no evidence of anticipatory or post-experiment effects in the treated group.

The analysis sample for 2SLS estimation of participation effects stacks data for two pairs of weeks: the first pair contains data on 1,600 drivers from the first two waves; the second pair includes observations from the two Taxi weeks for the 1,031 drivers who opted in to fee-free driving and agreed to receive Taxi offers later. The endogenous variable in this setup,  $D_{it}$ , indicates fee-free driving in week  $t$  or purchase of a Taxi contract during the Taxi opt-in weeks, to be used in week  $t$ . The instrument,  $Z_{it}$ , indicates offers of fee-free driving or a Taxi contract in

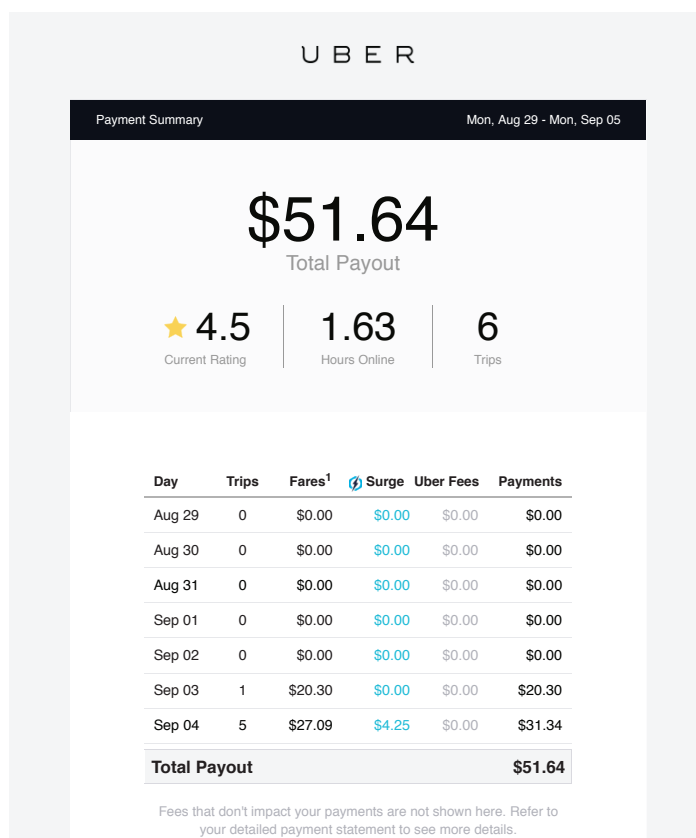


FIGURE 6. WEEKLY PAY STATEMENTS

*Notes:* This figure shows a weekly pay statement for a driver participating in the Earnings Accelerator. The column at the right lists net pay for each day.

week  $t$ . For example,  $Z_{i1}$  is switched on for the 800 drivers offered fee-free driving in Wave 1 and for the 619 drivers offered a Taxi lease during the first week of the Taxi trial.

For a set of weekly labor supply outcomes denoted by  $Y_{it}$ , the 2SLS setup used to compute participation effects can be written

$$(13) \quad Y_{it} = \alpha D_{it} + \beta X_{it} + \eta_{it},$$

$$(14) \quad D_{it} = \gamma Z_{it} + \lambda X_{it} + v_{it},$$

where  $X_{it}$  includes dummies indicating the strata used for random assignment, driver gender, the number of months a driver had worked on the Uber platform, one lag of log earnings, and indicators for whether a driver used Uber's vehicle leasing program and whether a driver had a car from model year 2003 or older. Because drivers appear in the sample more than once, standard errors in this setup are clustered by driver.

As can be seen in Figure 7, participation boosted participating drivers' hours and farebox considerably, with little effect on the extensive margin (that is, on an indicator for any Uber activity). The upper panel of the figure, which plots opt-in-week participation effects, also suggests that fee-free driving had no effect on participants' hours, farebox, and Uber activity rates in the week before Wave 1 or in the week following fee-free driving for Wave 2. In weeks of fee-free driving, however, participating drivers' hours and farebox rose by about 35 percent, though their Uber activity rates were almost unchanged. The estimates behind Figure 7, reported in panel A of online Appendix Table A5, show an effect of 0.04 on Uber activity during opt-in week. The absence of an effect before and after treatment weeks weighs against significant wealth effects from higher wages during treatment weeks.

The lower panel of Figure 7 shows that Taxi participation had a similar, though slightly smaller, effect on hours and farebox of around 30 percent. Effects on hours and earnings were smaller in the second week of Taxi than in the first, most likely reflecting the fact that the treatments offered that week were less generous. Online Appendix Table A5 shows that 2SLS estimates of participation effects are reasonably similar across hours groups. For example, the more precisely estimated effects in models with covariates show increases of 0.43 and 0.34 in the high and low hours groups in response to Taxi participation and 0.30 and 0.34 in the high and low groups during opt-in weeks. The estimated effect of Taxi participation on Uber activity is 0.01, and not significantly different from zero.

The fact that the farebox and earnings effects plotted in Figure 7 are similar suggests that Uber drivers face fairly constant rideshare earnings opportunities, as hypothesized in the theoretical discussion above. Online Appendix Table A6 reports 2SLS estimates of Earnings Accelerator participation effects on average hourly farebox and other measures of driver effort and labor supply, including the number of completed trips, the number of days worked during the week, the proportion of weekly trips earning a surge premium, and the average rating on rated trips during the week. Consistent with the hours and earnings estimates, these results show clear experimental effects on completed trips and the number of days driving. Effects on other outcomes, however, are small and not significantly different from zero. Online Appendix Figure A3 reports participation effects on the distribution of hours worked.

### B. *Estimating the Rideshare ISE*

The ISE for Rideshare hours is estimated by replacing the dependent variable in (13) with log hours driving, and replacing the endogenous variable in (14) with log wages earned as a driver. The hours variable,  $h_{it}$ , measures weekly hours with the Uber app toggled on; the wage,  $w_{it}$ , is the average hourly farebox net of Uber fees. The instruments are as before. The 2SLS estimate of the coefficient on  $\ln w_{it}$  is our measure of the ISE, denoted  $\delta^f$  in Section I (this is  $\tilde{\delta}$  in the model with alternative jobs). Life-cycle logic suggests wealth effects from leasing should be small, so offers of Taxi leasing and fee-free driving should generate similar ISEs when estimated in the same population.

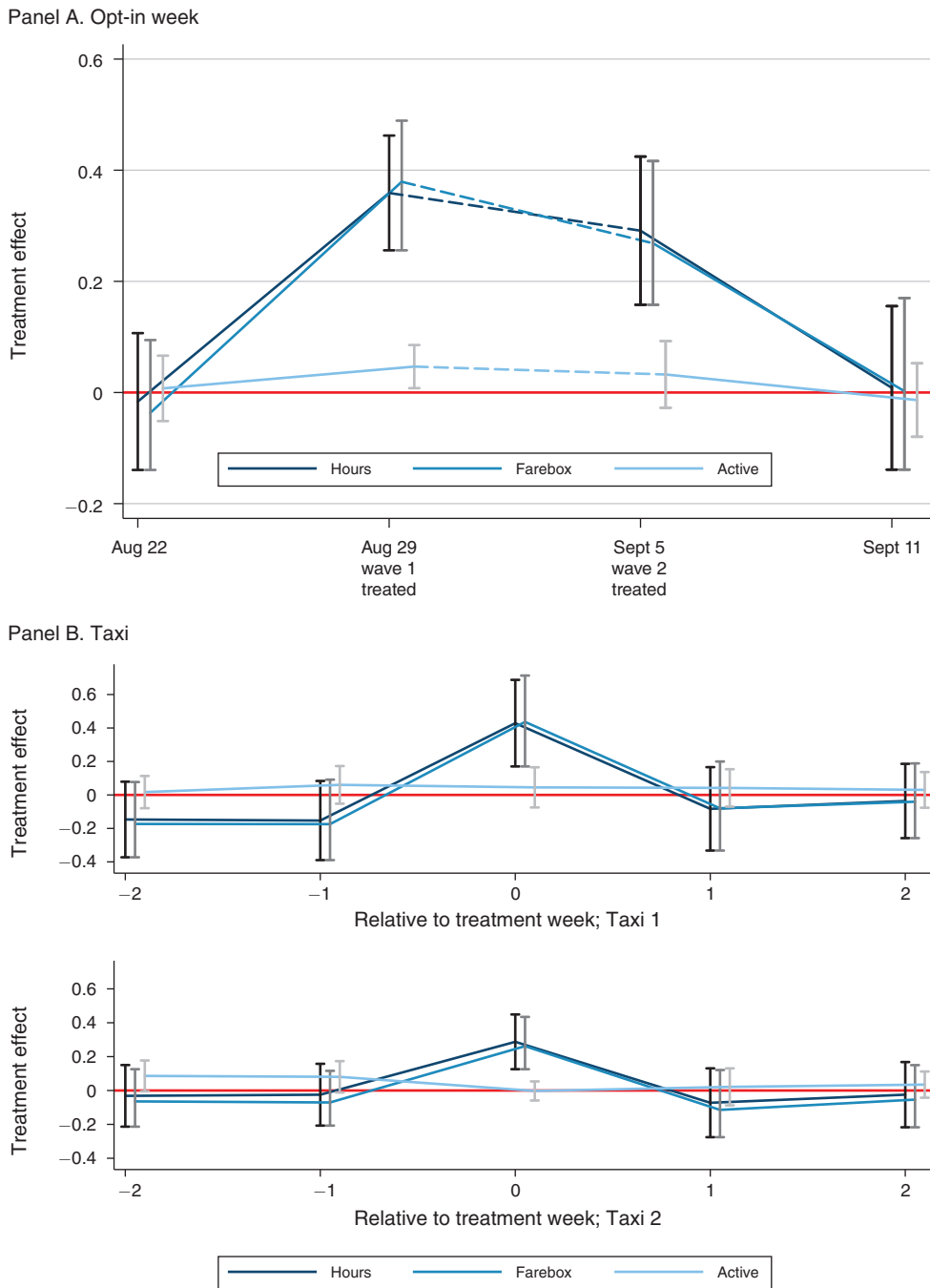


FIGURE 7. PARTICIPATION EFFECTS ON LABOR SUPPLY

*Notes:* This figure plots 2SLS estimates of Earnings Accelerator participation effects on hours, earnings, and an indicator of any Uber activity. Panel A reports estimated participation effects for drivers who accepted the opportunity to drive fee free. Panel B reports estimated participation effects for drivers who bought a Taxi lease. Effects are computed by instrumenting experimental participation with experimental offers as described in the text. Models control for the strata used for random assignment.



The first-stage effect of Earnings Accelerator offers on log wages ( $\gamma$  in equation (14)) depends on: (i) the experimental participation rate and (ii) the magnitude of experimentally induced fee changes. To see this, let  $w_{it}^0$  denote a driver's potential average hourly farebox in the absence of treatment. For a driver who pays fee  $t_1$  when treated and  $t_0$  otherwise, average hourly earnings can be written

$$\begin{aligned} w_{it} &= w_{it}^0(1 - t_0)(1 - D_{it}) + w_{it}^0(1 - t_1)D_{it} \\ &= w_{it}^0(1 - t_0) + w_{it}^0(t_0 - t_1)D_{it}. \end{aligned}$$

Ignoring covariates and using the fact that randomly assigned treatment offers are independent of  $w_{it}^0$ , the first-stage effect of offers on wages is

$$\begin{aligned} (15) \quad E[w_{it}|Z_{it} = 1, t_0, t_1] - E[w_{it}|Z_{it} = 0, t_0, t_1] \\ = (t_0 - t_1)E[w_{it}^0|D_{it} = 1] \times P[D_{it} = 1|Z_{it} = 1]. \end{aligned}$$

This shows that wages go up in the treatment group in an amount given by the experimental fee change times average wages for participants times the participation rate.<sup>10</sup>

The experimentally induced proportional change in wages is obtained by dividing (15) by average hourly earnings for controls,  $E[w_{it}|Z_{it} = 0] = E[w_{it}^0](1 - t_0)$ . Assuming wages are similar for participants and other drivers, a claim supported by Table 3, the proportional wage increase generated by the Earnings Accelerator is

$$\begin{aligned} (16) \quad \frac{E[w_{it}|Z_{it} = 1, t_0, t_1] - E[w_{it}|Z_{it} = 0, t_0, t_1]}{E[w_{it}|Z_{it} = 0, t_0, t_1]} \\ = \frac{(t_0 - t_1)}{1 - t_0} P[D_{it} = 1|Z_{it} = 1]. \end{aligned}$$

For example, with a take-up rate of  $2/3$ , the proportional first stage for an experiment that eliminates a 25 percent fee is roughly  $(0.25/0.75)0.66 = 0.22$ .<sup>11</sup>

Equation (16) is the first stage for a just-identified 2SLS estimator using a single dummy instrument for the log of net wages. Overidentified estimates using multiple instruments that distinguish different sorts of offers and different experimental weeks should generate more precise estimates. Fee-free driving offers were made twice, once each opt-in week, providing a pair of instruments to identify the ISE

<sup>10</sup>The derivation here uses the fact that  $D_{it} = 1$  implies  $Z_{it} = 1$ , which in turn yields  $E[w_{it}^0|D_{it} = 1, Z_{it} = 1] = E[w_{it}^0|D_{it} = 1]$ .

<sup>11</sup>The first stage in logs is  $\ln((1 - t_1)/(1 - t_0)) \times P[D_{it} = 1|Z_{it} = 1]$ , but  $\ln((1 - t_1)/(1 - t_0)) \approx (t_0 - t_1)/(1 - t_0)$ .

using data from opt-in weeks alone. Taxi offers produce 16 instruments, one for each lease, tax rate, and hours stratum in each of two Taxi weeks. We compute just-identified and overidentified estimates of the ISE in models controlling for random assignment strata and for a set of driver covariates listed in table notes. A parallel set of 2SLS estimates controlling only for strata appears in the online Appendix Table A7.

Just-identified estimates of the ISE range from about 1.2 using data from opt-in week to 1.8 in the Taxi sample. These estimates, reported in panel A of Table 5, are not too far from the experimentally identified ISE estimates reported for Swiss bicycle messengers by Fehr and Goette (2007).<sup>12</sup> The overidentified estimate of the (pooled-sample) ISE using Taxi variation falls to about 1.5, still larger than the corresponding estimate using data from opt-in weeks. It is perhaps unsurprising that drivers who find Taxi leasing attractive are more elastic.<sup>13</sup> In both samples, the just-identified and overidentified estimates are precise enough to rule out much smaller values. Moreover, we see little in the way of systematic elasticity differences between low- and high-hours drivers. It is also noteworthy that the corresponding OLS estimates of equation (13), reported in panel B, are far smaller than the ISEs identified by random assignment.

Two further comments on the impressively elastic behavior of Boston Uber drivers are in order. First, the ISE estimation sample omits drivers and weeks with no hours. Because Earnings Accelerator offers are largely unrelated to the decision whether to drive at all (a result shown in Figure 7), this extensive-margin conditioning seems innocuous.

Second, as discussed in the theoretical section, the increase in Uber effort induced by higher wages may come at the expense of work hours supplied elsewhere. Job shifting to take advantage of higher Uber wages leaves our welfare analysis unchanged (the relevant substitution elasticity reflects changes in Uber hours). But shifting in response to higher Uber pay means our estimates of the ISE can be expected to be larger than those estimated using data on total hours worked. The most elastic alternative job response is likely to be reduced hours driving for Lyft. The online Appendix therefore reports estimates for drivers less likely to shift away from Lyft. These estimates differ little from those discussed in the text.

#### IV. Taxi Participation

Figure 8 plots observed Taxi participation rates against predicted take-up for each of the sixteen Taxi contracts (four hours strata and commission groups times two treatments per group, in each of two weeks) offered to the sample of 1,031 drivers who opted in. Predicted participation is calculated using inequality (12), with the pre-experiment weekly farebox playing the role of  $wh_0$ . A value of  $\delta^f = 1.8$ , taken from column 4 in Table 5, is used to compute the driver surplus produced by higher

<sup>12</sup>Fehr and Goette (2007) estimate an ISE of between 1.12 and 1.25 for an all-male sample that is probably younger than our sample of Uber drivers.

<sup>13</sup>The argument that leads us to expect more elastic Taxi drivers parallels the phenomenon of self-selection in health insurance markets. Einav et al. (2013) argue that health insurance plans are chosen partly in view of anticipated healthcare utilization while covered by insurance.

TABLE 5—ESTIMATED ISEs

	Opt-in weeks			Taxi weeks		
	Pooled (1)	High hours (2)	Low hours (3)	Pooled (4)	High hours (5)	Low hours (6)
<i>Panel A. 2SLS estimates</i>						
First stage	0.20 (0.01)	0.19 (0.01)	0.21 (0.02)	0.13 (0.02)	0.11 (0.02)	0.15 (0.02)
2SLS	1.16 (0.12)	1.12 (0.16)	1.21 (0.19)	1.81 (0.37)	2.18 (0.66)	1.49 (0.44)
Over-identified model	1.17 (0.12)	1.12 (0.16)	1.23 (0.19)	1.48 (0.27)	1.46 (0.40)	1.54 (0.39)
<i>Panel B. OLS estimates</i>						
OLS	0.21 (0.06)	0.13 (0.08)	0.29 (0.09)	0.03 (0.08)	-0.05 (0.09)	0.13 (0.14)
Drivers	1,176	649	527	822	445	377
Observations	2,214	1,242	972	1,422	775	647

*Notes:* This table reports 2SLS estimates of the intertemporal substitution elasticity (ISE). The endogenous variable is log wages, instrumented with dummies indicating treatment offers. The overidentified estimates reported in columns 1–3 were computed using separate treatment indicators for each week, fee class, and hours group. Overidentified estimates in columns 4–6 uses separate treatment indicators for each taxi offer. All models control for the strata used for random assignment, time dummies, gender, whether a driver uses Uber’s Vehicle Solutions program, the number of months since Uber sign-up, vehicle older than 2003, and one lag of log earnings. Standard errors (reported in parentheses) are clustered by driver. A total of 1,600 drivers were offered fee-free driving in opt-in week; 1,031 accepted the offer and were eligible for Taxi leasing. Sample sizes in columns 1 and 4 are lower because the sample used to construct this table omit drivers with zero hours.

Taxi wages.<sup>14</sup> The regression of observed participation rates on predicted participation rates plotted in Figure 8 shows that empirical Taxi participation rates average well below predicted participation rates. Predicted participation is low for all hours and fee groups.

Perhaps the drivers who skipped Taxi did so because they correctly anticipated little benefit from a Taxi contract. This possibility is explored in Table 6, which reports average earnings gains for drivers who did and did not buy a Taxi lease. The sample here is limited to the 1,031 drivers who initially opted in. Columns 1–2 use the offer week earnings distribution to compute the earnings gains drivers could have expected under Taxi. Expected gains are computed using an ISE of 1.2, the estimate for opt-in-week participants (this adjustment is minor). For example, column 1 shows that 78 percent of drivers who accepted a Taxi contract would have expected to gain if they used offer week earnings to evaluate Taxi. This proportion is lower for those who did not buy a Taxi contract—56 percent in column 2—but still substantial. Among those expecting gains, the average gain amounts to \$92 for Taxi participants and \$66 for the nonparticipating group.

<sup>14</sup>Specifically, predicted participation rate for a treatment characterized by  $[L, t]$  is

$$\frac{1}{N_j} \sum_{i=1}^{N_j} \mathbf{1} \left\{ \log w h_{0i} > \log \left[ \frac{L}{t} \left( 1 + \frac{1}{2} \delta^f \frac{t}{1-t} \right)^{-1} \right] \right\},$$

where  $w h_{0i}$  is pre-experimental farebox for driver  $i$  in hours/commission group  $j$ , and  $N_j$  is the size of the group. This is computed for drivers who agreed to receive Taxi offers; that is, they opted in.

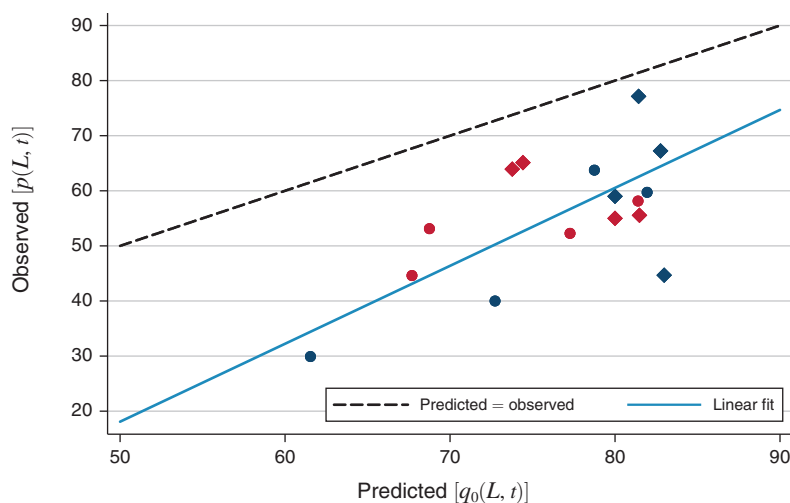


FIGURE 8. TAXI UNDERSUBSCRIPTION

*Notes:* For each of 16 strata defined by preexperimental hours driven, treatment week, and Taxi treatment offered, this figure plots empirical Taxi participation (lease purchase) rates against the theoretical rate predicted by the treated groups' earning distributions during opt-in week. Diamonds are used for the high hours group and circles are used for the low hours group. Red points are used for the 20 percent commission group and blue points are used for the 25 percent commission group. Drivers in the 20 percent commission group are more experienced than those in the 25 percent commission group. The ISE is set at 1.8. The dashed line indicates the locus of equality for theoretical and empirical take-up rates. Rates are calculated on the sample of drivers who drove during Taxi offer week.

Taxi participation gains forecast based on driving behavior during offer week are similar to those computed using the realized Taxi week earnings distribution. This can be seen by comparing the gains estimates in columns 1 and 2 of Table 6 with the estimates in columns 3 and 4 (column 3 uses realized gains for participants; column 4 is the expected gain for nonparticipants). Moreover, as can be seen in panel B of Table 6, conditional on driving (most drivers in the sample indeed drove, with or without Taxi), the expected gains from a Taxi contract among nonparticipants were a little *larger* than the gains anticipated or realized by participants. Compare, for example, \$103 and \$106 in anticipated benefits when forecast using the offer-week distribution and \$97 gained for participants and \$115 in expected gains foregone for nonparticipants using Taxi week data.

#### A. Risk Aversion and Lease Aversion

The after-the-fact gains from leasing that are documented in Table 6 weigh against the idea that drivers' private information accounts for low Taxi take-up. Perhaps risk aversion explains why so many drivers passed up a profitable opportunity to reduce their Rideshare fees in return for a modest payment. Risk aversion seems a natural hypothesis since fee elimination increases the proportional variance of earnings by  $1/(1 - t_0)^2$ . Rabin (2000) shows, however, that globally concave utility is unlikely to produce a coherent account of choices over small gambles like the one induced by our experiment (Chetty 2006 extends this argument to labor supply).

TABLE 6—GAINS AND LOSSES FROM TAXI

	Offer week earnings		Treatment week earnings	
	Expected		Observed	Expected
	Participated	Did not participate	Participated	Did not participate
	(1)	(2)	(3)	(4)
<i>Panel A. All</i>				
Mean benefit	\$92	\$66	\$85	\$64
Percent benefiting	78	56	85	54
Observations	560	679	560	679
<i>Panel B. Conditional on driving during treatment week</i>				
Mean benefit	\$103	\$106	\$97	\$115
Percent benefiting	83	78	92	87
Observations	515	423	515	423

*Notes:* This table reports the mean gains and losses from the Taxi treatment among treated drivers who did and did not buy a taxi contract. Columns 1 and 2 use data from Taxi offer weeks. Columns 3 and 4 use the same data, but adjust driver hours using the experimental wage offer and an ISE of 1.2. Panel A includes data for all treated drivers. Panel B includes data for drivers who drove during treatment week. The first row in each panel presents the mean gain for all workers in the sample. The second row reports the percent of workers benefiting.

The online Appendix uses data on expected gains and week-to-week farebox variation to calibrate the coefficient of relative risk aversion needed to explain low take-up among drivers for whom the expected gain from Taxi participation was positive. As in Sydnor's (2010) investigation of homeowners' choice of insurance deductibles, our calibration suggests drivers must be implausibly risk averse for concave utility alone to explain Taxi undersubscription.

On the other hand, loss aversion is a compelling explanation of low Taxi take-up: leasing might be a gamble that drivers hate to lose. The online Appendix sketches a simple model of loss aversion in the spirit of Fehr and Goette (2007) that yields a one-parameter modification of the rule given by (12). In this model, loss averse drivers treat a nominal lease cost of  $L$  as if this equals  $\kappa L$  for  $\kappa > 1$ . As in Andersen et al. (2014), our model of loss aversion postulates a time-varying reference point. In this case, it seems natural to assume that the potential earnings that would be realized under the default Rideshare contract determine the reference point for Taxi contracts. Drivers are modeled as averse to buying a Taxi contract that ends up reducing their earnings. This produces a kink in the utility of earnings when farebox crosses the Taxi breakeven.

*Parametric Lease Aversion.*—Loss aversion isn't necessary to explain lease aversion, but it does fit the facts.<sup>15</sup> The lease aversion hypothesis is evaluated here in the context of a model that describes how drivers predict their earnings. Our parametric forecasting model supposes that driver  $i$ 's forecast of his potential farebox,  $y_{0i} = wh_{0i}$ , is drawn from a log Normal distribution. Specifically, conditional on driver characteristics,  $X_i$ , forecast  $y_{0i}$  is assumed to be distributed according to

$$(17) \quad \ln y_{0i} | X_i \sim N(X_i' \beta, \tau_0^2),$$

<sup>15</sup>Chetty and Szeidl (2016) show that consumption commitments can also make moderate stakes gambles unattractive.

where  $X_i$  includes earlier earnings and our experimental stratification variables. Using this and inequality (9), the probability driver  $i$  participates in Taxi when offered a contract characterized by  $(L_i, t_i)$  can be written

$$\begin{aligned} q_0(L_i, t_i; X_i) &= 1 - \Phi \left[ \frac{\ln \frac{L_i}{t_i} + \ln \kappa - \sigma(t_i) - X_i' \beta}{\tau_0} \right] \\ &= \Phi \left[ \frac{1}{\tau_0} \left( \sigma(t_i) + X_i' \beta - \ln \frac{L_i}{t_i} \right) - \frac{1}{\tau_0} \ln \kappa \right], \end{aligned}$$

where  $\kappa$  parameterizes lease aversion and  $\sigma(t_i)$  is the proportional participation threshold reduction due to higher Taxi wages.<sup>16</sup> As for Figure 8,  $\sigma(t_i)$  is computed using  $\delta^f = 1.8$ .

Assuming forecasts are correct on average,  $\beta$  is identified by a regression of log farebox on  $X_i$  in the control sample. The parameters of primary interest in this model,  $\tau_0$  and  $\kappa$ , can then be estimated by inserting the regressor

$$\hat{w}_i = \hat{\sigma}(t_i) + X_i' \hat{\beta} - \ln \frac{L_i}{t_i},$$

into a probit model for take-up. Specifically, probit regressions of individual driver participation decisions on  $\hat{w}_i$  and a constant identify  $\tau_0$  and  $\kappa$  as transformations of the slope and intercept in the probit function

$$(18) \quad P[D_i = 1 | L_i, t_i, X_i] = \Phi \left( \frac{1}{\tau_0} \hat{w}_i - \frac{1}{\tau_0} \ln \kappa \right).$$

This model allows forecast earnings variance to differ from the empirical earnings variance (that is, the variance identified by (18) need not match the variance of the earnings forecast regression associated with (17)). The possibility of extra variance in forecast earnings can be motivated as reflecting drivers' subjective view of his or her earnings variability.

We start with a version of (18) with an estimate of  $\hat{w}_i$  obtained by regressing the log of offer week farebox (for control drivers) on a set of covariates,  $X_i$ , that includes lags farther back. As can be seen in the first column of Table 7, the resulting estimate of  $\kappa$  is about 1.4, with an estimated forecast standard deviation roughly twice as large than the root mean-squared error (RMSE) of the forecasting regression, (17). An online theoretical Appendix shows that  $\kappa = 1.4$  implies a coefficient of loss aversion around 2, not far from estimates reported in Tversky and Kahneman (1991).

Columns 2–4 of Table 7 report estimates from models incorporating a forecasting equation that predicts farebox during the week Taxi drivers exploited their lease rather than during offer week. Columns 2, 3 and 4, respectively, report the results of adding one, two, and three further farebox lags to the list of predictors in  $X_i$ .<sup>17</sup> The

<sup>16</sup>For example, a driver in the  $t_0$  fee class at Uber who was offered a zero fee has  $\sigma(t_i) = \ln \left[ 1 + (\delta^f t_0 / (2(1 - t_0))) \right]$ .

<sup>17</sup>The forecasting models used here include indicators for each of the eight hours  $\times$  fee  $\times$  week strata. Lag coefficients vary by the week offered Taxi. Lagged log earnings are set to zero when lagged earnings are zero;

resulting estimates of  $\kappa$ , shown along with bootstrapped standard errors computed as described in the online empirical Appendix, are remarkably stable at around 1.4 across specifications. Estimates of the standard deviation of the forecast distribution exceed the RMSE of the error in the regression used to predict wages. These estimates suggest that driver uncertainty includes an idiosyncratic component beyond the conditional cross-sectional variance of earnings. At the same time, this extra uncertainty is insufficient to rationalize Taxi undersubscription.<sup>18</sup>

*Nonparametric Lease Aversion.*—Control drivers' earnings are sampled from the distribution of  $y_{0i}$ . The extent of driver lease aversion is therefore identified without recourse to a parametric model for  $y_{0i}$ . To see this, note that incorporating lease aversion in the participation rule given by (9), drivers buy a Taxi lease if

$$\ln y_{0i} > \ln \frac{L}{t} + \ln \kappa - \sigma(t),$$

for any distribution of  $\ln y_{0i}$ . Writing  $p_{Lt}$  for the Taxi participation rate among drivers offered  $[L, t]$ , this rule implies

$$1 - p_{Lt} = F_0\left(\ln \frac{L}{t} + \ln \kappa - \sigma(t)\right),$$

where  $F_0$  is the control drivers' log farebox distribution. Distribution function  $F_0$  can then be inverted to produce a quantile regression that identifies  $\kappa$ :

$$(19) \quad \underbrace{F_0^{-1}(1 - p_{Lt})}_{\text{nonparticipation quantile}} = \ln \kappa + \ln \frac{L}{t} - \sigma(t).$$

The dependent variable here is the nonparticipation quantile for the sample of drivers offered  $[L, t]$ , that is, the farebox value that has  $p_{Lt}$  of drivers above and  $1 - p_{Lt}$  of drivers below it.

Figure 9 plots the sample analog of  $F_0^{-1}(1 - p_{Lt})$  against  $\ln(L/t) - \sigma(t)$  for our 16 Taxi treatment combinations. Without lease aversion (i.e.,  $\kappa = 1$ ), the quantiles plotted on the y-axis should be close to the log breakeven minus an adjustment for driver response to higher Taxi wages ( $\sigma(t)$ ), with deviations from this value due solely to sampling variance. The black line in the figure is the 45-degree line marking these points. As can be seen in the figure, however, nonparticipation quantiles systematically exceed the adjusted log breakeven. The average gap between predicted and treated quantiles is summarized by the blue regression line, which has slope equal to that generated by a weighted regression of nonparticipation quantiles

models include missing data dummies for this. The second lagged farebox for the first Taxi trial includes data from the week in which Wave 2 drove fee free. The third lagged farebox for the first Taxi trial includes data from the week in which Wave 1 drove fee free. Probit estimation generates a slope (the coefficient on  $\hat{w}_i$ ) and an intercept. Parameter  $\tau$  is estimated as the reciprocal of the slope. Parameter  $\kappa$  is estimated using this estimate and the value of the intercept.

<sup>18</sup>Table A8 in the online Appendix, which reports estimates of (18) by subgroup, shows little evidence of heterogeneity in  $\kappa$  by hours driven.



TABLE 7—MODELING TAXI TAKE-UP

	Parametric				Inattention	
	(1)	(2)	(3)	(4)	(5)	(6)
Slope	0.69 (0.10)	0.73 (0.09)	0.81 (0.09)	0.79 (0.09)	0.69 (0.10)	0.68 (0.10)
Intercept	-0.24 (0.07)	-0.25 (0.07)	-0.28 (0.07)	-0.27 (0.07)	-0.24 (0.07)	-0.17 (0.09)
Implied Kappa	1.41 (0.11)	1.40 (0.10)	1.41 (0.10)	1.41 (0.10)	1.41 (0.11)	1.27 (0.15)
Implied Tau	1.46 (0.22)	1.36 (0.18)	1.24 (0.15)	1.26 (0.16)	1.46 (0.22)	1.47 (0.23)
Forecasting regression RMSE	0.71	0.82	0.80	0.79	0.71	0.71
Attentive					1.00 (0.00)	
Attentive × low hours						0.91 (0.06)
Attentive × high hours						1.00 (0.01)
Number of drivers	954	938	938	938	954	954
Earnings distribution	Predicted offer week	Predicted treatment week	Predicted treatment week	Predicted treatment week	Predicted offer week	Predicted offer week
Number of earnings lags	1	1	2	3	1	1

Notes: Parametric models are fit to micro data on take-up using equation (18) in the text. Standard errors are bootstrapped as described in the online Appendix.

on  $\ln(L/t) - \sigma(t)$ , with weights given by the number of treated drivers in each hours stratum. Although the estimated slope here is close to one, the empirical quantiles are clearly shifted up, implying that drivers typically set a bar well above the theoretical breakeven when deciding on a Taxi lease.

The intercept generated by the blue line in the figure implies a value of  $\kappa$  equal to about 1.6 (that is,  $e^{0.45}$ ). This estimate is similar to those from the parametric model of Taxi take-up, though considerably less precise. Whiskers in the figure denote 95 percent confidence intervals, computed using bootstrapped standard errors.<sup>19</sup> Because the nonparametric estimates are less precise than the parametric, parametric estimates are employed in the CV calculations discussed below.

### B. Accounting for Inattention

As in the Mas and Pallais (2017) analysis of worker response to various sorts of job offers, a simple alternative to the lease aversion story is driver inattention to the

<sup>19</sup>These are calculated by drawing bootstrap samples of treated and control drivers, stratifying by commission, treatment group, and week, and estimating  $\kappa$  nonparametrically for each bootstrap sample.

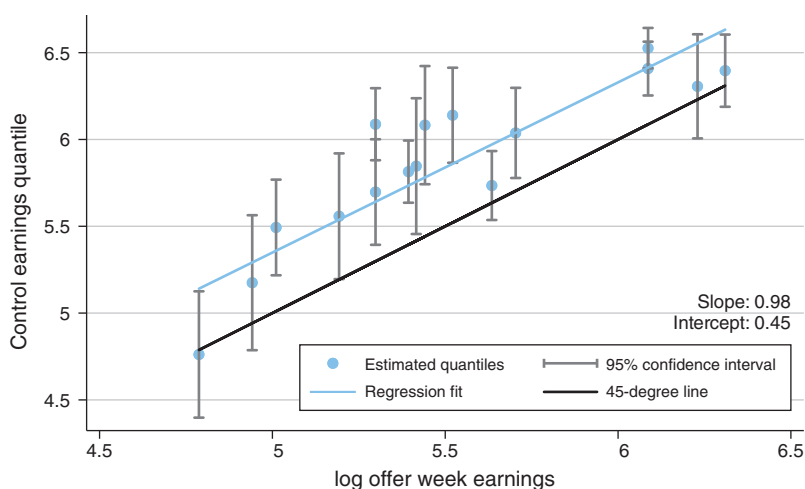


FIGURE 9. COMPARING EMPIRICAL AND THEORETICAL PARTICIPATION QUANTILES

*Notes:* For each of 16 strata defined by pre-experimental hours driven, treatment week, and Taxi treatment offered, this figure plots the quantile of offer week earnings for the control group against the log of theoretical offer week earnings, defined as breakeven minus a labor supply adjustment. Control earnings quantiles are calculated from the sample of drivers who drove during offer week. Whiskers indicate 95 percent confidence intervals for each quantile. A weighted regression line fit to the plotted points appears in blue. A 45-degree line is plotted in black.

details of Earnings Accelerator lease offers. Perhaps some drivers failed to notice or understand our proffered Taxi contracts.

As noted above, the Earnings Accelerator promotion was deployed in phases in part to identify drivers attentive to Uber's extensive promotional messaging. In particular, only drivers who opted to participate in the no-risk opt-in-week phase were offered Taxi contracts. But some opt-in-week drivers may nevertheless have missed or ignored follow-up Taxi offers. This provides an alternative explanation for Taxi undersubscription.

We model inattentive behavior by modifying participation equation (18) to include a fraction that ignores Taxi messaging. Letting this fraction be denoted by  $\phi$ , the theoretical Taxi participation probability becomes

$$(20) \quad (1 - \phi) \Phi \left[ \frac{1}{\tau_0} \left( \sigma(t_i) + X_i' \beta - \ln \frac{L_i}{t_i} \right) - \frac{1}{\tau_0} \ln \kappa \right].$$

Inattention can be distinguished from lease aversion because the former is modeled as a fixed proportion of behavioral take-up, while the latter is additive and inside the probit function, with an effect that implicitly depends on covariates.

Columns 5 and 6 of Table 7 present estimates of two versions of this augmented model, one where  $\phi$  is constrained to be equal for all drivers (shown in column 5) and one where  $\phi$  varies with baseline hours (shown in column 6). Results in both columns show little evidence of inattention among participating drivers. Moreover, the estimates of  $\kappa$  generated by models allowing for inattention differ little from those generated by the simpler model. Note also that lease aversion adds a constant

amount to the nonparticipation quantile predicted by the surplus-adjusted breakeven. Figure 9 indeed seems consistent with this hypothesis. Finally, results not reported here explore specifications allowing the probability that a worker is attentive to vary as a function of gender, experience driving for Uber, and pre-experimental hours driven. These results are consistent with the estimates in columns 5 and 6 of Table 7.

## V. Compensating for Leasing

We use estimates of the ISE and  $\kappa$  to compute average weekly CV for the sample of 19,316 active Boston drivers described in column 1 of Table 1. This sample drives more and therefore has higher weekly earnings than the sample of experiment-eligible drivers, which is limited to those with average weekly hours between 5 and 25. Conditional on driving, the average weekly farebox in the Boston active sample is \$541 in July 2016; weekly earnings are about \$423. This exceeds the average farebox (and earnings) in Table 1 because here the average is over weeks rather than over drivers and because the average omits weeks with zero earnings. Dropping zeros sidesteps the issue of how or whether to compensate inactive drivers who buy a lease. On one hand, we might assume that future inactive drivers neither drive Rideshare nor lease, in which case their CV is zero; alternately, as in our experiment, inactive drivers who buy a lease might be presumed to be stuck with it, in which case their CV should equal the lease price. The CV calculation for active drivers uses equation (4), with  $\delta^f = 1.2$  and  $\kappa = 1.4$ , which are representative of our findings for the full sample.

Table 8 shows average weekly CV computed for a range of possible Rideshare-Taxi wage gaps and leases. We interpret wage gaps as generated by Rideshare fees, though these gaps might also reflect fare differences under alternative transportation regulations. CV gives the weekly payment required to make a driver as well off under Taxi-style leasing as under an Uber-style fee arrangement. As can be seen in panel A of Table 8, for weekly lease rates in the range of the 2010 Boston lease cap of \$700, the average compensation needed to make a driver indifferent between Rideshare and Taxi ranges from \$166 with  $L = 600$  and a wage difference of 50 percent, to \$710 when  $L = 800$  and the wage gap is only 15 percent.

With a 25 percent fee and a lease cost of \$600, perhaps a realistic scenario, average CV is \$437. Almost all active drivers have positive CV in this case (negative CV indicates drivers prefer Taxi; the third entry in each cell indicates the proportion of drivers who prefer Rideshare to Taxi). About 10 percent of drivers who bought a Taxi contract did not drive in the week covered by their lease. These drivers presumably meant to drive when they bought the lease, but were precluded from doing so, perhaps for reasons related to health or family. Rideshare is especially attractive when the risk of not driving is high.<sup>20</sup>

With lower lease costs, CV is naturally smaller; in low-lease-price scenarios, Taxi may well be a better deal. For a lease rate of \$150, for example, a wage gap of 25 percent makes leasing attractive to many, with average CV equal to  $-\$13$ . Even

<sup>20</sup>Lease payments were not refunded to drivers who did not drive.

so, 59 percent still prefer Rideshare in this scenario (median CV is \$35; medians are reported in the second row of each cell in Table 8). With a lease price of only \$100 and a fee of 20 percent, many drivers (45 percent) prefer Taxi.

A natural point of comparison between the two contracts is the lease price that sets CV equal to 0, that is, the lease rate that leaves drivers indifferent between Rideshare and Taxi. As can be seen in column 8, this averages from \$90 with a 15 percent wage gap to \$434 with a 50 percent wage gap. These maximum lease values are equal to the (average of the) sum of the fees that would be paid to Uber without leasing plus the surplus generated by higher Taxi wages. In the notation of equation (4), this quantity is  $t_0 w h_0 (1 + (\delta t_0 / (2(1 - t_0))))$ .

Behavioral lease values are calibrated to be 40 percent above nominal (since  $\kappa = 1.4$ ), with the resulting CV calculation summarized in panel B of Table 8. Assuming Rideshare fees of 25 percent or less, lease aversion makes CV positive even for a lease cost of only \$150. The Rideshare contract in this case generates CV of \$47, though 50 percent higher Taxi wages make Taxi attractive to most drivers (38 percent still prefer Rideshare in this case). A lease of \$116 equates Rideshare and Taxi with a 25 percent fee. Even with a lease as low as \$100, however, most (57 percent) lease averse drivers prefer Rideshare to Taxi given a 25 percent fee.

As can be seen in column 5 of panel B, with a \$400 lease and a 25 percent wage difference, median CV is \$445, more than the nominal lease. The excess of CV over the nominal lease can be interpreted as an interest payment to drivers in return for lending the local Taxi and Limousine Commission (or other lease-granting authority) the value of the lease until compensation is paid (presumably 1–2 weeks after lease purchase, that is, the week after leased driving is completed). Interest of \$45 on a \$400 loan for a week or two sounds high, but is not out of line with the \$15 fee typically paid for a \$100 payday loan.<sup>21</sup>

The comparisons in Table 8 implicitly make driving Taxi a condition for receipt of compensation. An alternative compensation scenario allows former Rideshare drivers to quit driving when Rideshare work disappears, receiving UI instead (this is fanciful since Rideshare drivers who stop driving may not qualify for UI). The dollar compensation required to make idle Rideshare drivers as well off as they were when driving for Rideshare is reported in online Appendix Table A9, along with the proportion expected to take this option.

Online Appendix Table A9 shows that the UI option reduces the cash compensation required to make former rideshare drivers indifferent to the disappearance of the rideshare compensation scheme. Importantly, however, the UI compensation option also slashes consumer (rider) welfare by reducing the supply of drivers. With a \$200 lease and a 25 percent wage difference for example, 48 percent of non-lease-averse drivers take advantage of the opportunity to receive compensation without driving (the proportion sitting out appears in the second line of each cell). This reduces the number of hours supplied to the market by 17 percent (these figures appear in the third row of each cell).

<sup>21</sup>The cost of payday loans is described in <http://libertystreeteconomics.newyorkfed.org/2015/10/reframing-the-debate-about-payday-lending.html>.

TABLE 8—COMPENSATING VARIATION

Wage gap (Rideshare fee)	Weekly lease rates							Max lease
	\$50 (1)	\$100 (2)	\$150 (3)	\$200 (4)	\$400 (5)	\$600 (6)	\$800 (7)	
<i>Panel A. Nominal lease</i>								
15 percent	-\$40	\$10	\$60	\$110	\$310	\$510	\$710	\$90
	-\$13	\$37	\$87	\$137	\$337	\$537	\$737	
	42%	66%	80%	89%	99%	100%	100%	
20 percent	-\$75	-\$25	\$25	\$75	\$275	\$475	\$675	\$125
	-\$38	\$12	\$62	\$112	\$312	\$512	\$712	
	33%	55%	69%	79%	97%	100%	100%	
25 percent	-\$113	-\$63	-\$13	\$37	\$237	\$437	\$637	\$163
	-\$65	-\$15	\$35	\$85	\$285	\$485	\$685	
	26%	46%	59%	70%	91%	98%	100%	
50 percent	-\$384	-\$334	-\$284	-\$234	-\$34	\$166	\$366	\$434
	-\$256	-\$206	-\$156	-\$106	\$94	\$294	\$494	
	10%	20%	29%	37%	59%	74%	83%	
<i>Panel B. Behavioral lease</i>								
15 percent	-\$20	\$50	\$120	\$190	\$470	\$750	\$1,030	\$64
	\$7	\$77	\$147	\$217	\$497	\$777	\$1,057	
	54%	78%	90%	96%	100%	100%	100%	
20 percent	-\$55	\$15	\$85	\$155	\$435	\$715	\$995	\$89
	-\$18	\$52	\$122	\$192	\$472	\$752	\$1,032	
	43%	66%	80%	89%	100%	100%	100%	
25 percent	-\$93	-\$23	\$47	\$117	\$397	\$677	\$957	\$116
	-\$45	\$25	\$95	\$165	\$445	\$725	\$1,005	
	35%	57%	71%	81%	98%	100%	100%	
50 percent	-\$364	-\$294	-\$224	-\$154	\$126	\$406	\$686	\$310
	-\$236	-\$166	-\$96	-\$26	\$254	\$534	\$814	
	14%	27%	38%	47%	71%	85%	92%	

Notes: Panel A shows compensating variation (CV, paid to Rideshare drivers to induce them to work under a Taxi contract), computed for the nominal lease rates listed in columns 1–7. Column 8 reports the mean lease price at which drivers are indifferent between Taxi and Rideshare. Panel B evaluates CV using behavioral lease rates computed from Taxi take-up. The behavioral lease is 40 percent greater than the nominal lease. The ISE is set at 1.2. The first row of each cell shows average CV. The second row shows median CV. The third row reports the proportion of drivers with positive CV, meaning they prefer Rideshare. CV is evaluated using weekly earnings and hours data for all Boston Uber drivers working in the month of July 2016 who completed at least 4 trips. Weeks with zero trips are omitted. The mean farebox conditional on driving is \$541.

With lease averse drivers, UI cuts service by almost a third. By contrast, the CV calculation that requires Taxi driving as a condition for compensation leaves rider welfare improved or unchanged (in fact, the driving requirement weakly increases trip supply). The non-UI scenario is also fiscally attractive: in principle, a benevolent Taxi and Limousine Commission can implement the CV scheme described in Table 8 using the revenue from leasing, with some money left over. Historically, however, the revenue from medallion sales has not been redistributed to drivers. It is also worth noting that a long-term, unanticipated removal of rideshare work opportunities may have income effects, meaning the relevant elasticity for welfare calculations is smaller. A smaller labor supply elasticity makes Taxi less attractive, increasing the compensation required when rideshare work disappears.<sup>22</sup>

<sup>22</sup>CV is also larger if labor supply is less elastic to the ride-hailing industry as a whole than to individual platform operators (Caldwell and Oehlsen 2018). But the drivers in our sample earn over 90 percent of their ride-hailing income

## VI. Summary and Directions for Further Work

The economic consequences of alternative work arrangements depend in large part on the response of work effort to pay. A high labor supply elasticity makes lease-based contracts more attractive since workers that are more responsive to pay gain more from higher wages. On the other hand, the kind of lease aversion documented here, a context-specific form of loss aversion, increases the compensation needed to induce leasing.

The experiment analyzed here generates an ISE on the order of 1.2 in the full sample and 1.8 for drivers who opted in to leasing. These values are too small to overcome many drivers' lease aversion. Consequently, the compensation required to make drivers indifferent to the loss of Rideshare-type earnings opportunities far exceeds the already mostly positive CV computed using nominal lease rates. Perhaps surprisingly, the response to wage changes and lease offers varies little across strata defined by hours worked and commission rates (which vary with experience). This suggests the estimates reported here may be reasonably representative of Uber driver behavior.

Our estimates of the value of a proportional compensation model come from a sample of Uber drivers who agreed to consider such contracts. Evidence for lease aversion in other settings comes from the New York City TLC, which has experimented with "Fare Share Leasing," a scheme that allows drivers to lease a medallion by paying "a percentage of a driver's farebox revenue," much like the Uber fee.<sup>23</sup> This pilot is in response to a TLC survey highlighting the "stress associated with starting shifts 'in the red' having paid a set lease price at the beginning of shifts." Interest in alternatives to leasing for Taxi drivers may be accelerated by electronic payments and app-based dispatching, technology that inhibits misreporting of the farebox.

Our economic analysis focuses on drivers. In principle, however, the experimental Taxi scheme evaluated here creates enough additional surplus to allow drivers and platform owners to negotiate a lease-based contract that is Pareto superior to commission-based compensation schemes like the Uber fee. As is the case with any system that taxes output, the social cost of the Rideshare contract arises from the wedge proportional fees insert between wages and effort. Medallion leasing can be seen as a classic solution to the problem of efficient contracting (see, e.g., Lazear 2018). Lease revenue is therefore adequate to compensate drivers who might prefer relatively efficient Taxi-style contracts. But this compensation possibility presumes drivers will indeed accept nominal CV in return for leasing.

Lease aversion may explain why the evolving ride-hailing market seems to have only briefly flirted with virtual leasing of the sort explored in our experiment. In 2016, Boston rideshare upstart Fasten offered its drivers an \$80 lease in return for "weekly unlimited driving," that is, driving with no fee. Fasten's other compensation scheme took a fee equal to a dollar a trip; this probably amounts to an average fee of around 10 percent. As can be seen in panel B of Table 8, with a 15 percent fee, any

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from Uber (Koustas 2018). This suggests our CV calculation for a sample of Uber drivers is not too wide of the mark.

<sup>23</sup>See [https://www1.nyc.gov/assets/tlc/downloads/pdf/taxicab\\_leasing\\_resolution.pdf](https://www1.nyc.gov/assets/tlc/downloads/pdf/taxicab_leasing_resolution.pdf) for details.



lease under \$90 is attractive. Fasten's \$80 lease therefore seems like it should have been attractive to many drivers. But this conclusion is overturned by lease aversion, which reduces the maximum lease rate that drivers will pay to avoid a 15 percent fee to \$64. It is unsurprising, therefore, that Fasten appears to have had few takers for weekly unlimited driving.<sup>24</sup>

Finally, it is interesting to compare our results with the Mas and Pallais (2017) estimates of workers' willingness to pay for job amenities. Their findings suggest workers place little value on hours flexibility for its own sake, though workers prefer to avoid jobs that let employers control work schedules. These findings seem consistent with the notion that it is the need to pay lease costs up front rather than hours constraints that make leasing distasteful. Looking down the road, a natural direction for future research is the interaction between contractual differences and market structure. More competition between service providers presumably means a more elastic labor supply response to individual platform operators. This in turn should make Taxi contracts like those offered in our experiment more attractive.

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<sup>24</sup>Fasten ended operations in the United States in early 2018.



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