Uber vs. Taxi: A Driver's Eye View*

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Abstract

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 benefitted 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.

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1 Introduction

Traditional 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, limited supply had turned medallions into valuable assets, typically held by investors or fleet owners, and trading for 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're 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.[1] 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 looks at the economic value of rideshare work opportunities, focusing on differences in the compensation arrangements available to traditional taxi and rideshare drivers. We assess these compensation models from a driver's point of view with the aid of an experiment that offered random samples of Boston Uber drivers a virtual lease that eliminates or reduces the Uber fee. Some lease-paying drivers were offered a negative fee, capturing a possibly higher taxi wage. The response to our offers reveals a large, precisely estimated intertemporal substitution elasticity (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), and belie claims that taxi driver labor supply is mediated by an empirically important degree of income targeting as argued in, e.g., Camerer et al. (1997).[2] Our estimated substitution elasticities are also in line with the Mas and Pallais (2018) experimental estimates of

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

[2]See Farber (2005; 2015) for more on taxi driver supply elasticities.

compensated elasticities for part-time workers with flexible hours.

The labor supply elasticity is a key parameter in our evaluation of the rideshare compensation contract. A large intertemporal substitution elasticity tends to make medallion-type contracts more attractive since elastic drivers collect additional surplus by driving longer hours when their hourly wage goes up. And 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, a phenomenon we call "lease aversion." To quantify lease aversion, we compute a behavioral lease parameter that rationalizes empirical lease take-up rates. The ISE and lease aversion are the key economic parameters that determine the level of compensating variation required when a rideshare scheme is replaced by leasing. Even without lease aversion, the opportunity to drive with no lease payment generates considerable surplus for most of the Uber drivers in our sample unless lease prices fall below about $100 per week. In the face of a $200 weekly lease, lease aversion increases Boston drivers' average rideshare surplus to nearly one-third of their Uber earnings.

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 rideshare work opportunities for drivers, our theoretical framework and empirical strategy are relevant for any job where the "right to work" can be purchased at either a flat rate or by giving up a share of earnings. There are many such settings. Service professionals like hair stylists and cosmetologists face this sort of choice, for example, either 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 formalizes economic differences between the taxi and rideshare compensation schemes. Section 3 describes our experimental design and context. Section 4 presents estimates of drivers' labor supply elasticities. Section 5 analyzes the Taxi take-up decision and argues that low take-up is explained by loss aversion. Section 6 discusses estimates of compensating variation, comparing rideshare and leasing. Section 7 concludes.

2 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% or 25% of its drivers gross fares (referred to here as the "farebox"; these are base fares received 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.[3]

2.1 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" implicit in the two contracts.

[3]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 "up front pricing." Lyft has experimented with similar schemes. Neither rideshare platform requires drivers to make advance payments analogous to medallion leasing, though some rideshare upstarts such as Fasten have tried such schemes.

Our experiment ran for one week at a time, and many drivers indeed lease weekly, so it's 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 $t_0 = .25$, 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 by driving longer hours, thereby clearing breakeven. This scenario is sketched in Figure 2. As in Ashenfelter (1983)'s 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

$$e(p, w, \bar{u}) \equiv \min_{x,l} px + wl \ s.t. \ u(x, l) = \bar{u},$$

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.

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

$$s(w, u_0) + L < s(w_0, u_0), \tag{1}$$

where $w_0 = w(1 - t_0)$ is the after-fee Uber wage. Using 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

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

where h_0 is Rideshare labor supply (we omit the superscript reminding us this is the level of work determined by the compensated supply function).

It's useful to rewrite the Taxi participation rule in terms of of the Taxi breakeven:

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

where δ 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

$$\frac{1}{1+.5\delta\frac{t_0}{1-t_0}}.$$

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%, for example, we expect the participation threshold to be reduced relative to breakeven by $1 - \frac{1}{1+.25/2\times.75} \approx 14.5\%$.

2.2 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

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

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).

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 over-compensate for Taxi because the Taxi scheme increases wages, yielding additional driver surplus. The term $w h_0 \frac{\delta t_0}{2(1-t_0)}$ in equation (4) captures this surplus. The surplus generated by higher Taxi wages is the product of the proportional Taxi wage advantage, $\frac{t_0}{1-t_0}$, the substitution elasticity (δ), and the driver's 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.

Sitting Out

The compensation formula above presumes Rideshare drivers accept the Taxi budget line as a condition for compensation. But we might also allow former Rideshare drivers to refuse Taxi, taking some of their compensation in the form of increased leisure. Drivers who make this choice end up at the origin in Figure 3. They're made whole by UI in an amount that takes them to the u_0 ordinate, a scenario illustrated in Figure 4.

To compute the UI needed in this case, we assume the marginal utility of leisure is zero at $h = 0$, so drivers with a wage of zero choose 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:

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

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

$$UI = (1 - t_0)wh_0 - \frac{1}{2}\left(\frac{\partial h^c}{\partial w}\frac{w(1 - t_0)}{h_0}\right)([1 - t_0]wh_0) \tag{6}$$

$$= (1 - t_0)wh_0\left[1 - \frac{\delta}{2}\right] \tag{7}$$

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% since their $\delta = 0$.

2.3 Life Cycle Considerations

We compare Rideshare and Taxi in a multi-period setting using the Browning et al. (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 or intertemporal substitution elasticity (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

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

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.[4]

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

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

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

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

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

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

Using the expansion yielding equation (8), this becomes:

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

This is the same as (4), with the ISE δ^f again replacing the substitution elasticity, δ. Since the ISE (weakly) exceeds the Hicks substitution elasticity, a life-cycle perspective tends to

[4] Our streamlined notation also ignores the 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.

favor Taxi. Because our experimental design offers temporary wage changes, we interpret the experiment as identifying δ^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. Knowing how much a driver drives in response to each wage, a predicted wage implies a predicted farebox. Our econometric framework (outlined in Section 5, below) embeds farebox prediction in an empirical model for Taxi participation.

2.4 Don't Quit Your Day Job

The drivers in our experiment can typically supply as many hours to Uber as they like at the implicit market wage, but many Rideshare drivers work at another job (Hall and Krueger, 2017). We model movement between a single Rideshare employer and alternative employment as motivated by declining earnings opportunities on the alternative job. 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.[5]

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

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

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, when faced

[5]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.

with driving (Rideshare or Taxi) wage w and parameters L, t, 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: $f^a(w, \bar{u}; 0, L) = (px^c + L) - wh^c - e(a^c) = s^a(w, \bar{u}) + L$,

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

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

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

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

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

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 analyses unchanged.

3 Experimental Design

Uber and its ride-hailing competitors routinely offer drivers temporary increases in pay ("promotions") that are designed to equilibrate supply and demand without the need for surge pricing. Riders are typically unaware of these changes in driver pay. We estimate Rideshare labor supply elasticities and lease aversion parameters using a randomized experiment pitched to drivers as an Uber promotion called the *Earnings Accelerator*.

3.1 Overview

The Earnings Accelerator unfolded in three phrases: (1) selection and notification of eligible drivers, (2) opt-in weeks, and (3) Taxi treatment weeks. Drivers were eligible for inclusion in the experiment if they took at least four trips in the month prior to sample selection and if they drove an average of 5-25 hours per week in the month prior to selection. The omission of higher 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. Higher hours drivers may differ from other drivers, of course. But our analysis of drivers grouped by hours driven within the eligible sample shows little systematic variation in the behavioral parameters that go into the computation of CV.

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% 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.

Eligible drivers were randomly selected for inclusion in the experiment within strata defined by average hours driven in July, driver fee class (commission rate), and vehicle model year.[6] The low hours stratum includes drivers who averaged 5-15 hours per week in July, while the high hours group averaged 15-25 hours per week. The 20% fee class includes veteran drivers who signed up before September 2015, while others pay the current Boston commission rate of 25%. 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. We also report the proportion of drivers with cars newer than 2010 because 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

[6]More precisely, the relevant month for this purpose ran from the last 3 weeks of July 2016 through the first week of August 2016.

of the eligible sample.

3.2 Opt-In Weeks

A total of 1600 drivers were selected randomly from the eligible pool. Half in this sample (Wave 1) were offered a week of fee-free driving in the first opt-in week. While the first wave was driving fee-free, drivers the second half sample (Wave 2) were offered the opportunity to opt in for fee-free driving the following week. Thus, the wealth effect of experimental wage changes are roughly balanced across waves. Appendix Table A1 sketches the experimental timeline. Appendix Table A2 shows that driver characteristics are well balanced across waves.

Drivers in both waves were offered fee-free driving by e-mail, text message and in-app notification on Monday morning of the relevant opt-in 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% in the 20% fee class ($.25 = \frac{1}{.8} - 1$) and by 33% in the 25% fee class ($.33 = \frac{1}{.75} - 1$).

Roughly sixty-four percent of drivers (1031/1600) accepted our offer of fee-free driving, reflecting a take-up rate of 71% in Wave 1 and 58% in Wave 2. Lower take-up in Wave 2 likely reflects the fact that we stopped reminding most drivers to opt-in mid-week during the second opt-in week (this was a budgetary consideration). Opt-in statistics for each of the free week strata are reported in Table 2.

Higher wages should be attractive to all drivers, but Uber drivers receive many electronic messages. Some of these messages are likely ignored.[7] Drivers who opted in consented for their data to be used in academic research and to receive further Earnings Accelerator offers. Discussions with Uber's Boston team suggest Earnings Accelerator take-up rates compare favorably with the response rate to other no-lose driver promotions requiring an opt-in.

Table 3 shows that drivers who opted in drove and earned more than other drivers during the opt-in week. In the pooled sample including both high and low hours drivers, those who opted in had an opt-in-week farebox roughly $100 higher than the farebox of drivers who

[7] In view of this, Uber has moved recently to cap the number of promotion-related messages sent to drivers.

opted out. Those who opted-in also drove 4 more hours that week. On the other hand, these gaps are much smaller when averaged over the month of July. It's also noteworthy that drivers who agreed to participate in the Earnings Accelerator look to be otherwise similar to those who opted out. We see little difference in average commission rates, percent female, or months on platform, for example.

3.3 Taxi Treatments

The 1031 drivers who opted in to fee-free driving were randomly offered Taxi treatments in one or both of two weeks. Taxi treatments were also randomly assigned within strata defined by average hours and fee. The experiment offered eight treatments in each Taxi week, two for each hours/fee combination. Appendix Tables A3 and A4 show that random assignment balanced the characteristics of drivers in the Taxi treatment and control groups.

Taxi treatments consist of a fee reduction, $t_1 - t_0$, and a lease price, L. Lease rates and fee changes for both weeks of the Taxi trial are listed in Table 4. In the first Taxi week, 40% of drivers in each stratum were offered the opportunity to buy another week of fee-free driving and 20% were offered negative fee driving in the form of a 12.5% wage increase ($t_1 = -.125$). 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 week 2 treatment was offered to 30% of drivers within strata. These design parameters are summarized in Figure 5.

As was done with solicitation for fee-free driving in opt-in week, drivers were offered Taxi contracts via e-mail, text message and in-app notification. The messages making these offers were sent one week in advance and highlighted the breakeven amount. For example, drivers in the 25% 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 that clicked through to a simple table showing the revised fee calculation for a sample trip. Emails and text messages also included links that clicked through to a calculator that showed net earnings with and without the Earnings Accelerator for any driver-selected value of fares+surge. Figure (A1) shows a message delivered in the Taxi promotions; Figure (A2) shows the calculator.

Experimental lease rates and fee changes were designed to be attractive to about 60% of drivers in each stratum; in practice, about 45% accepted the offer of a Taxi contract. Lease payments were deducted from opt-in week pay and appeared as a negative entry on weekly pay statements on the line that shows any (usually positive) payment drivers might have earned through Uber promotions. These deductions were labeled "Earnings Accelerator buy-in." It's worth noting that drivers did not have to wait for a weekly pay statement to see the benefits of fee reductions: these were visible as soon as any reduced-fee trip was completed.

Our experimental 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 prices were calibrated to appeal to drivers with weekly earnings in particular ranges, as explained below. As a measure of the contemporary empirical relevance of our design, it's 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.[8]

4 Labor Supply Effects

4.1 Impacts on Participants

Our estimates of the ISE rely on a linear labor supply model for drivers with positive hours driven. We preface these estimates with a set of results using offers as instruments 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 1600, participants are drivers who agreed to be in the experiment during the opt-in phase. Second, for the 1031 drivers who opted in, participants are those who purchased a Taxi contract. Participation estimates distinguish extensive from

[8]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 entrenched (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/) quotes a pre-ride-hailing Boston medallion price of over $700,000, down recently to about half 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).

intensive margin effects, identify possible changes in average hourly compensation, and reveal any possible anticipatory or post-treatment labor supply changes that might signal confounding wealth effects. The participation analysis yields three important findings: (1) Earnings Accelerator participation had no effect on the extensive margin (that is, effects on whether drivers drive at all); (2) Participation boosted hours driven and driver earnings considerably during treatment weeks, increases that are proportional, with no corresponding change in average hourly earnings; (3) 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 1600 drivers from the first two waves; the second pair includes observations from the two Taxi weeks for the 1031 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 week t. For example, Z_{i1} is switched on for the 800 drivers offered fee-free d riving 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 for ISE estimates can be written:

$$Y_{it} = \alpha D_{it} + \beta X_{it} + \eta_{it} \tag{13}$$

$$D_{it} = \gamma Z_{it} + \lambda X_{it} + \upsilon_{it}, \tag{14}$$

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 hours, and indicators for whether a driver used Uber's "vehicle solutions" 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 on driver.

As can be seen in Figure 7, fee-free driving and Taxi offers both boosted participating drivers' hours and farebox considerably, with little effect on the extensive margin (that is, on an indicator for any Uber activity, $wh_{it} > 0$). The upper panel of the figure also suggest that fee-free driving had no effect on participants' hours, farebox, and Uber activity rates in the week before Wave 1 (this is opt-in week for 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%, though their extensive margin activity rates were almost unchanged. The estimates behind Figure 7, reported in appendix Table A5 show an effect of .04 on Uber activity during opt-in week. The absence of an effect before and after treatment weeks weighs against any wealth effect from higher wages during one of the two treatment weeks.

The lower panel of Figure 7 shows that the Taxi treatment had a similar, though slightly smaller, effect on hours and farebox of around 30%. Effects on hours and earnings were smaller in the 2nd week of Taxi than in the first, most likely reflecting the fact that the treatments offered that week were less generous. 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 .40 and .34 in the high and low hours groups in response to Taxi participation and .33 and .35 in the high and low groups during opt-in weeks. The estimated effect of Taxi participation on Uber activity is .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 Section 2.4. 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 with any driving. Effects on other outcomes, however, including average hourly farebox and ratings, are small and not significantly different from zero. Appendix Figure A reports participation effects on the distribution of hours worked.

4.2 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 var 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 2SLS estimate of the coefficient on $\ln w_{it}$ is our measure of the ISE, denoted δ^f in Section 2 (this is the parameter $\tilde{\delta}$ 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.

The first stage effect of Earnings Accelerator offers on log wages (γ in equation 14) depends on: (1) the experimental participation rate, and (2) the magnitude of experimentally-induced fee changes. To see this, let w^0_{it} denote a driver's potential average hourly farebox in the absence of treatment. Participation decisions determine average hourly earnings through

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

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

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

In other words, wages go up in the treatment group in an amount given by the experimental fee change times average wages for participants times the opt-in rate.[9]

The experimentally-induced proportional change in wages is obtained by dividing (15) by average hourly earnings for controls, $E[w_{it}|Z_{it}=0] = E[w^0_{it}](1-t_0)$. 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:

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

In other words, the proportional first stage for wages is the experimentally-induced change in fee divided by the baseline take-home rate, times the treatment take-up rate. For example, with a take-up rate of 2/3, the proportional first stage for an experiment that eliminates a

[9] The derivation here uses the fact that $D_{it}=1$ implies $Z_{it}=1$, which in turn yields $E[w^0_{it}|D_{it}=1, Z_{it}=1] = E[w^0_{it}|D_{it}=1]$.

25% fee is roughly $\frac{.25}{.75}.66 = .22$.[10]

Equation (16) is the first stage for a just-identified 2SLS estimator using a single dummy instrument. Over-identified 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 in each opt-in week, providing a pair of instruments to identify the ISE using data from opt-in weeks. 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 over-identified 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 appendix.

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).[11] The over-identified estimate of the (pooled-sample) ISE using Taxi variation falls to about 1.4, still larger than the corresponding estimate using the full sample. It's perhaps unsurprising that drivers who find Taxi leasing attractive are more elastic.[12] In both samples, the just-identified and over-identified 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's 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 with no hours in a given week. Because Earnings Accelerator offers are largely unrelated to drivers' decisions as to whether to be active at all (a result shown in Figure 7), this extensive-margin conditioning seems innocuous.[13]

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

[11]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.

[12]The argument that leads us to expect more elastic Taxi drivers parallels the phenomenon of selection on moral hazard in health insurance markets. Einav, Finkelstein, Ryan, Schrimpf and Cullen (2013) argue that health insurance plans are chosen partly in view of anticipated healthcare utilization while covered by insurance.

[13]Models that control for lagged earnings and hours also include dummies for those missing these variables

Second, as discussed in Section 2.4, the increase in Uber effort 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 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. An appendix on platform substitution therefore reports estimates for drivers less likely to shift away from Lyft. These estimates differ little from those discussed in the text.

5 Taking Taxi

Figure 7 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 1031 drivers who opted in. Predicted participation is calculated using (12), with the pre-experiment opt-in week 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 Taxi wages. [14] The regression of observed participation rates on predicted participation rates plotted in Figure 7 shows that empirical Taxi participation rates average well below predicted.

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 us limited to the 1031 drivers who initially opted-in. Columns 1-2 use the opt-in 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 Earnings Accelerator participants (this

in lagged weeks.

[14]This is the estimate for drivers participating in the experiment (that is, they agreed to receive Taxi offers). Figure 7 uses fareboxes of control drivers in the same hours stratum and commission as treated drivers. The predicted participation rate for a treatment characterized by $[L, t]$ is

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

where wh_{0i} is opt-in week farebox for driver i in hours/commission group j, and N_j is the size of the group. This rate therefore conditions on positive hours during opt-in week.

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 opt-in 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 non-participating group.

It's noteworthy that Taxi participation gains forecast based on driving behavior during opt-in 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 non-participants). However, 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 non-participants were a little *larger* than the gains anticipated or realized by participants. Compare, for example, 103 and 106 dollars in anticipated benefits when forecast using the opt-in week distribution and 97 dollars gained for participants and **115** dollars in expected gains foregone for non-participants using Taxi week data.

5.1 Risk Aversion and Lease Aversion

Drivers' private information does not appear to account 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 $\frac{1}{(1-t_0)^2}$. 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).

The 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 (2010)'s 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: lease purchase looks to be a gamble that drivers hate to lose. The 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 is really equal to κL 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 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.[15] The lease aversion hypothesis is evaluated in combination with 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:

$$\ln y_{0i} | X_i \sim N(X_i' \beta_0, \tau_0^2), \tag{17}$$

where X_i includes opt-in week and/or earlier earnings and our experimental stratification variables. Using this and (9), the probability driver i participates in Taxi when offered (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 κ is the behavioral lease rate, $\sigma(t_i)$ is the proportional participation threshold reduction due to higher Taxi wages, and (L_i, t_i) describes the Taxi contract offered to this driver.[16] Again, $\sigma(t_i)$ is computed using $\delta^f = 1.8$.

Assuming forecasts are correct on average, β is identified from a regression of log farebox

[15] Chetty and Szeidl (2016) show that consumption commitments can also make moderate stakes gambles unattractive.

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

on X_i in the control sample. The parameters of primary interest in this model, τ_0 and κ, 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 τ_0 and κ as transformations of the slope and intercept in this conditional probability function

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

This model allows forecast earnings variance to exceed the empirical earnings variance. The extra variance in forecast earnings can be motivated by the fact that many drivers will not have known their full opt-in week farebox at the time they decided to lease (most participation decisions were made shortly after receiving the first communication presenting a Taxi offer).

We start with a version of (18) implemented by regressing the log of opt-in 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 κ 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) (compare .71 and 1.45). The 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. Columns 2, 3 and and 4, respectively, report the results of adding one, two, and then three further farebox lags to the list of predictors in X_i.[17] The resulting estimates of κ, shown along with bootstrapped standard errors computed as described in the empirical appendix, are remarkably stable at around 1.4 in all specifications. Estimates of the standard deviation of the forecast distribution are again quite a bit larger than the RMSE of the corresponding forecasting variance. These estimates suggest that driver uncertainty indeed includes an idiosyncratic component

[17] All forecasting models include indicators for each of the eight hours $\times$ fee $\times$ week strata. Lag coefficients vary by week offered Taxi. Lagged log earnings are set to zero when lagged earnings are zero; models include missing data dummies for this occurrence. The 2nd lagged farebox for the first Taxi trial includes data from the week in which Wave 2 was driving fee free. The 3rd lagged farebox for the first Taxi trial includes data from the week in which Wave 1 was driving fee free. See appendix Figure A1 for timing details.

beyond the conditional cross-sectional variance of earnings. At the same time, this extra uncertainty is insufficient to rationalize Taxi undersubscription.

Nonparametric Lease Aversion

Control drivers' earnings are sampled from the distribution of y_{0i}. The extent of driver lease aversion is therefore identified without need of 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

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

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 κ:

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

The dependent variable here is the non-participation 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 8 plots the sample analog of $F_0^{-1}(1 - p_{Lt})$ against $\ln \frac{L}{t} - \sigma(t)$ 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 forty-five degree line marking these points. As can be seen in the figure, however, non-participation 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 non-participation quantiles on $\ln \frac{L}{t} - \sigma(t)$, 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 higher than the theoretical breakeven when deciding to buy a Taxi lease.

The intercept generated by the blue line in the figure implies a value of κ equal to about

1.6 (that is, $e^{.45}$). This estimate is similar to those from the parametric model of Taxi take-up, though considerably less precise. Whiskers in the figure denote 95% confidence intervals, computed using bootstrapped standard errors.[18] Because the non-parametric estimates are less precise than the parametric, parametric estimates are employed in the CV calculations discussed below.

Attending to Inattention

As in the Mas and Pallais (2018) analysis of worker response to various sorts of job offers, a simple alternative to the lease aversion story is driver inattention to the details of Earnings Accelerator lease offers. Perhaps some drivers failed to notice or understand our proffered Taxi contracts.

In this context, it's noteworthy that the Earnings Accelerator experiment included only drivers attentive enough to accept our initial no-lose offer of a week of fee-free driving. Even so, some participating drivers may have missed or ignored follow-up offers. We allow for this possibility by modifying participation equation (18) to include a fraction ϕ that ignores Earnings Accelerator offers. This generates a participation probability of

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

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 presents estimates of two versions of this augmented model, one where ϕ is constrained to be equal for all drivers (shown in column 5) and one where ϕ varies with baseline hours (shown in column 6). Results in both columns suggest we needn't worry about inattention. Likewise, the estimates of κ these models generate is not much different from our baseline estimates of lease aversion. Note also that a nonparametric version of these findings amounts to the claim that the non-participation quantile on the left-hand side of (19) should be shifted additively from the surplus-adjusted breakeven. Figure 8 indeed seems consistent with this hypothesis. Finally, results not reported here explore

[18] These are calculated by drawing bootstrap samples of treated and control drivers, stratifying by commission, treatment group, and week, and estimating κ nonparametrically for each bootstrap sample.

specifications allowing the probability a worker is attentive to vary as a function of gender and experience on the Uber platform, as well as hours worked. These are are consistent with the estimates in Columns 5 and 6 of Table 7.

6 Compensating Taxi

We use estimates of the ISE and lease aversion coefficient 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 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 we're averaging over weeks rather than over drivers and omitting 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 we can likewise see these gaps as reflecting fare differences under alternative transportation regulations. 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%, to \$710 when $L = 800$ and the wage gap is only 15%.

With a 25% 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 (recall that negative CV indicates drivers prefer Taxi; the third entry in each cell indicates the proportion of drivers who prefer Rideshare to leasing). About ten 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 buying a lease, but were precluded from doing so, perhaps for reasons related to health or family.

With lower lease costs, CV is naturally smaller; in low-lease scenarios, Taxi may well be a better deal. For a lease rate of \$150, for example, a wage gap of 25% makes leasing attractive to many, with average CV equal to -\$13, though 59% 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%, most drivers (55%) prefer Taxi.

A natural summary measure of CV 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% wage gap up to \$434 with a 50% 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 $t_0 w h_0 (1 + \frac{\delta t_0}{2(1-t_0)})$.

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

As can be seen in column 5 of Panel B of Table 8, with a \$400 lease and a 25% 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 not out of line with the \$15 fee typically paid for a \$100 payday loan.[19]

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

[19] The cost of payday loans is described in http://libertystreeteconomics.newyorkfed.org/2015/10/reframing-the-debate-about-payday-lending.html.

drivers who stop driving don't currently qualify for UI). As noted at the end of Section 2.2, UI cuts the monetary cost of compensation by allowing former Rideshare drivers to take additional leisure. The dollar compensation required to make idle Rideshare drivers as well off as they were when driving for Rideshare is reported in Appendix Table A8, along with the proportion expected to take this option.

Appendix Table A8 shows that the UI option reduces the cash compensation required to make former rideshare drivers indifferent to the disappearance of rideshare work opportunities. Importantly, however, the UI compensation option also slashes consumer (rider) welfare by reducing rideshare services. With a $200 lease and a 25% wage difference for example, 48% 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% (these figures appear in the third row of each cell).

In the UI version of this scenario with lease averse drivers, UI cuts service by almost a third. Because CV-compensated drivers are necessarily just as well off either way, the contrast that requires Taxi driving as a condition for compensation comes closer to a welfare comparison focused on drivers, while leaving 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 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's 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.[20]

[20]CV is also larger if labor supply is less elastic to the ride-hailing industry as a whole than to individual platform operators. The distribution of total rideshare hours worked may differ from the distribution of Uber hours. But in our data, Uber drivers appear to earn over 90% of their ride-hailing income from Uber (Koustas, 2017). This suggests our CV computation for a sample of Uber drivers is not too wide of the mark.

7 Summary and Directions for Further Work

Compensation schemes create incentives integral to work arrangements of many kinds. A key parameter governing the economic consequences of alternative work arrangements is the response of work effort to pay. In the market for transportation services, a high labor supply elasticity makes taxi leasing contracts more attractive since elastic drivers gain more from higher wages. On the other hand, lease aversion increases the compensation needed to induce leasing. Our randomized Taxi experiment identifies an ISE on the order of 1.2 in the full sample and 1.8 for drivers who opted in to the experiment. These values are not large enough 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.

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 Uber contract arises from the wedge the Uber fee inserts between wages and effort. Medallion leasing effectively "sells the firm to the worker," a classic solution to the problem of efficient contracting (see, e.g., Lazear 1995, 2018). As long as drivers are required to accept the Taxi contract as a condition for compensation, any necessary transfer can be funded by lease revenue. But this possibility presumes drivers will indeed accept nominal CV in return for leasing.

It's also interesting to compare our results with the Mas and Pallais (2018) estimates of workers' willingness-to-pay for job amenities. Their findings suggest workers place little value on hours flexibility for it's own sake, though they prefer to avoid jobs that grant employers discretion when setting work schedules. These findings seem consistent with the notion that it's the need to pay lease costs up front rather than hours constraints that make leasing distasteful.

Our results hint at why the rapidly evolving ride-hailing market seems to have only briefly flirted with virtual leasing of the sort explored in our Earnings Accelerator 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 around 10%. As can be seen in Panel B of Table 8, with a 15% fee, any lease under $90 is attractive. Fasten's $80 lease therefore seems likely to have been in the ballpark for many drivers. But this conclusion is overturned by lease aversion, which reduces the maximum lease rate that drivers will pay to avoid a 15% fee to $64. It's unsurprising, therefore, that Fasten appears to have had few takers for weekly unlimited driving. Other evidence for lease aversion comes from developments at the New York City TLC, which recently began piloting "Fare Share Leasing" allowing drivers to lease a medallion by paying "a percentage of a driver's farebox revenue", much like the Uber fee.[21]

Looking down the road, a natural direction for further research on ride-hailing labor markets is an exploration of how the economic consequences of contractual differences interact with market structure, such as the presence of competing ride-hailing services. 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 ours more attractive (*ceteris paribus*). It is also interesting to consider contractual comparisons from the point of view of driver populations that may be more or less elastic, such as men and women, and those who do and do not own their own vehicles. We are exploring these questions in ongoing work.

[21]See http://www.nyc.gov/html/tlc/downloads/pdf/taxicab_leasing_resolution.pdf for details.

Table 1: Boston Uber Drivers

	All Boston Drivers (1)	Eligible Drivers (2)	Experimental Drivers (3)	Strata-Adjusted Difference (4)
Female	0.14	0.14	0.14	0.00
	(0.35)	(0.34)	(0.35)	(0.01)
Age	40.90	41.58	41.80	0.15
	(12.13)	(12.20)	(12.29)	(0.36)
Hours Last Week of July	14.99	13.86	15.72	0.42
	(16.27)	(10.49)	(11.26)	(0.28)
Average Hours/Week in July	14.42	13.13	14.51	0.06
	(14.39)	(5.69)	(5.81)	(0.08)
Average Hourly Earnings in July	15.39	17.59	17.40	-0.10
	(8.64)	(6.19)	(6.05)	(0.17)
Average Weekly Farebox in July	372.06	310.91	342.82	-0.80
	(447.51)	(192.04)	(198.12)	(3.93)
Months Since Sign-up	13.89	14.26	11.14	-0.08
	(9.43)	(9.25)	(8.67)	(0.15)
Vehicle Solutions	0.08	0.08	0.08	0.01
	(0.26)	(0.27)	(0.28)	(0.01)
Car Model Year 2003 or Older	0.03	0.03	0.12	0.00
	(0.17)	(0.17)	(0.33)	(0.00)
Car Model Year 2011 or Newer	0.64	0.64	0.56	-0.01
	(0.48)	(0.48)	(0.50)	(0.01)
Commission	22.34	22.24	23.21	0.00
	(2.50)	(2.49)	(2.40)	(0.01)
Number of Observations	19316	8685	1600	8685

Note: 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 treated drivers. Treatment was randomly assigned within strata defined by hours (high/low), commission (20/25% commission) and car age (older/newer than 2003). Column 4 shows the strata-adjusted difference between the treated sample and the eligible pool. Average hourly earnings include surge but are net of fee. Vehicle solutions drivers lease a car through an Uber-sponsored leasing program.

Table 2: Earnings Accelerator Opt-In Week Parameters and Take-up

Group			Offers		Opt-Ins	
Hours	Car	Fee	Number	Rate	Number	Rate
(1)	(2)	(3)	(4)	(5)	(6)	(7)
			Wave 1			
High	New	20%	102	6%	75	74%
	New	25%	202	17%	155	77%
	Old	--	96	100%	61	64%
		--	400	13%	291	73%
Low	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	New	20%	150	8%	84	56%
	New	25%	250	21%	154	62%
		--	400	13%	238	60%
Low	New	20%	250	9%	133	53%
	New	25%	150	6%	89	59%
		--	400	7%	222	56%
			800		460	

Table 3: Who Opts In?

	Pooled		High Hours		Low Hours	
	Opt-Out Mean	Strata-Adjusted Difference	Opt-Out Mean	Strata-Adjusted Difference	Opt-Out Mean	Strata-Adjusted Difference
	(1)	(2)	(3)	(4)	(5)	(6)
Female	0.13	0.03	0.12	0.01	0.14	0.05*
	[0.33]	(0.02)	[0.32]	(0.02)	[0.35]	(0.03)
Age	42.75	-1.46**	44.81	-3.06***	40.89	-0.08
	[12.61]	(0.65)	[12.68]	(0.95)	[12.27]	(0.89)
Commission	23.11	0.16	22.97	0.33*	23.24	0.00
	[2.43]	(0.13)	[2.46]	(0.18)	[2.39]	(0.17)
Vehicle Solutions	0.06	0.03**	0.07	0.04**	0.05	0.02
	[0.24]	(0.01)	[0.26]	(0.02)	[0.23]	(0.02)
Vehicle Year	2010.40	-1.76	2010.56	-3.50	2010.26	0.06
	[4.45]	(1.96)	[4.39]	(3.82)	[4.51]	(0.33)
Months Since Signup	11.60	-0.71	12.53	-1.61**	10.75	0.09
	[9.03]	(0.46)	[9.19]	(0.67)	[8.81]	(0.63)
Hours Worked Week Starting 08/22	11.28	4.01***	16.07	2.56**	6.93	4.86***
	[13.35]	(0.69)	[14.48]	(1.06)	[10.51]	(0.79)
Farebox Week Starting 08/22	251.50	99.93***	358.77	71.83***	153.95	114.05***
	[306.38]	(16.07)	[340.60]	(25.15)	[232.39]	(17.91)
Average Hours/Week in July	14.16	0.53*	19.67	-0.18	9.16	0.49**
	[6.01]	(0.31)	[3.01]	(0.22)	[2.84]	(0.21)
Average Hourly Earnings in July	16.19	1.88***	17.46	2.30***	15.03	1.26***
	[5.56]	(0.30)	[4.80]	(0.38)	[5.95]	(0.45)
Average Weekly Farebox in July	310.06	50.85***	447.65	57.13***	184.93	24.36***
	[180.52]	(9.90)	[145.18]	(11.48)	[100.90]	(7.54)
Number of Observations	569	1600	271	800	298	800

Note: 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. Average hourly earnings include surge but are net of fee. Vehicle solutions drivers lease a car through an Uber-sponsored leasing program.

Table 4: Earnings Accelerator Taxi Parameters and Take-up

Group			Treatment			Offers and Opt-Ins	
Hours	Fee	No. in Group	Lease	New Fee	Break-even	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

Note: 60% of each stratum was offered treatment each week. Opt-in rates are reported as a proportion of drivers offered.

Table 5: Estimated ISEs

	Opt-In Week			Taxi		
	Pooled	High Hours	Low Hours	Pooled	High Hours	Low Hours
	(1)	(2)	(3)	(4)	(5)	(6)
			A. 2SLS Estimates			
First Stage	0.20***	0.19***	0.21***	0.13***	0.11***	0.15***
	(0.01)	(0.01)	(0.02)	(0.02)	(0.02)	(0.03)
2SLS	1.18***	1.13***	1.23***	1.81***	2.09***	1.56***
	(0.12)	(0.16)	(0.20)	(0.37)	(0.63)	(0.45)
Over-identified	1.19***	1.14***	1.25***	1.43***	1.31***	1.62***
Model	(0.12)	(0.16)	(0.19)	(0.25)	(0.35)	(0.38)
			B. OLS Estimates			
OLS	0.34***	0.26***	0.42***	0.20**	0.11	0.31**
	(0.06)	(0.08)	(0.08)	(0.09)	(0.11)	(0.14)
Drivers	1176	649	527	821	445	376
Observations	2214	1242	972	1421	775	646

Note: This table reports 2SLS estimates of the intertemporal substitution elasticity (ISE). The endogenous variable is log wages, instrumented with dummies indicating treatment offers. The over-identified model in columns 1-3 uses separate treatment indicators for each week, fee class, and hours group. The over-identified model in columns 4-6 uses separate treatment indicators for each taxi offer. These offers vary by week, treatment group, fee class, and hours group. 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 sign-up, whether the car is older than 2003, and one lag of log hours. Standard errors are clustered by driver. A total of 1600 drivers were offered fee-free driving in opt-in week; 1031 accepted the offer and were eligible for Taxi leasing. Sample sizes in columns 1 and 4 are lower because the data used to construct this table omit zeros.

Table 6: Gains and Losses from Taxi

	Opt-In Week Earnings		Live Week Earnings	
	Expected		Observed	Expected
	Participated	Did Not Participate	Participated	Did Not Opt-In
	(1)	(2)	(3)	(4)
	A. All			
Mean Benefit	$92	$66	$85	$64
Percent with Positive Benefit	78%	56%	85%	54%
Observations	560	679	560	679
	B. Conditional on Driving During Live Week			
Mean Benefit	$103	$106	$97	$115
Percent with Positive Benefit	83%	78%	92%	87%
Observations	515	423	515	423

Note: This table reports the median 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 opt-in week. 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 live week. The first row in each panel presents the mean gain for all workers in the sample. The second row presents the percent of workers with positive gains. The third row presents the median gain for drivers with positive gains.

Table 7: Modeling Taxi Take-Up

	Parametric				Inattention	
	(1)	(2)	(3)	(4)	(5)	(6)
Slope	0.69***	0.73***	0.81***	0.79***	0.69***	0.68***
	(0.09)	(0.09)	(0.08)	(0.08)	(0.09)	(0.10)
Intercept	-0.23***	-0.24***	-0.27***	-0.26***	-0.24***	-0.18*
	(0.07)	(0.07)	(0.07)	(0.07)	(0.07)	(0.09)
Implied Kappa	1.40***	1.38***	1.39***	1.39***	1.41***	1.29***
	(0.11)	(0.10)	(0.09)	(0.10)	(0.10)	(0.15)
Implied Tau	1.45***	1.36***	1.24***	1.26***	1.46***	1.47***
	(0.19)	(0.17)	(0.13)	(0.13)	(0.20)	(0.21)
Forecasting regression RMSE	0.71	0.82	0.80	0.79	0.71	0.71
Attentive					1.00***	
					(0.00)	
Attentive * Low Hours						0.92***
						(0.06)
Attentive * High Hours						1.00***
						(0.01)
Number of Drivers	954	938	938	938	954	954
Earnings Distribution	Predicted Opt-In Week	Predicted Live Week	Predicted Live Week	Predicted Live Week	Predicted Opt-In Week	Predicted Opt-In Week
Number of Earnings Lags	1	1	2	3	1	1
Covariates	Yes	Yes	Yes	Yes	Yes	Yes

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 appendix. Each column uses data from the control drivers' earnings distribution.

Table 8: Compensating Variation for Loss of Rideshare

	Weekly Lease Rates							
	\$50	\$100	\$150	\$200	\$400	\$600	\$800	Max Lease
Wage Gap	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
				A. Nominal Lease				
	-\$40	\$10	\$60	\$110	\$310	\$510	\$710	\$90
15%	-\$13	\$37	\$87	\$137	\$337	\$537	\$737	
	42%	66%	80%	89%	99%	100%	100%	
	-\$75	-\$25	\$25	\$75	\$275	\$475	\$675	\$125
20%	-\$38	\$12	\$62	\$112	\$312	\$512	\$712	
	33%	55%	69%	79%	97%	100%	100%	
	-\$113	-\$63	-\$13	\$37	\$237	\$437	\$637	\$163
25%	-\$65	-\$15	\$35	\$85	\$285	\$485	\$685	
	26%	46%	59%	70%	91%	98%	100%	
	-\$384	-\$334	-\$284	-\$234	-\$34	\$166	\$366	\$434
50%	-\$256	-\$206	-\$156	-\$106	\$94	\$294	\$494	
	10%	20%	29%	37%	59%	74%	83%	
				B. Behavioral Lease				
	-\$20	\$50	\$120	\$190	\$470	\$750	\$1,030	\$64
15%	\$7	\$77	\$147	\$217	\$497	\$777	\$1,057	
	54%	78%	90%	96%	100%	100%	100%	
	-\$55	\$15	\$85	\$155	\$435	\$715	\$995	\$89
20%	-\$18	\$52	\$122	\$192	\$472	\$752	\$1,032	
	43%	66%	80%	89%	100%	100%	100%	
	-\$93	-\$23	\$47	\$117	\$397	\$677	\$957	\$116
25%	-\$45	\$25	\$95	\$165	\$445	\$725	\$1,005	
	35%	57%	71%	81%	98%	100%	100%	
	-\$364	-\$294	-\$224	-\$154	\$126	\$406	\$686	\$310
50%	-\$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 Taxi), computed for the nominal lease rates listed in columns 1-7. Column 8 reports the mean lease that makes a driver indifferent between Taxi and Rideshare. Panel B evaluates CV using behavioral lease rates computed from Taxi take-up. The behavioral lease is fifty 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. CV is evaluated using weekly earnings and hours data for all Boston Uber drivers in the month of July who completed at least 4 trips. Weeks with zero trips are omitted. The mean farebox conditional on driving is 541. The mean payout conditional on driving is 423.

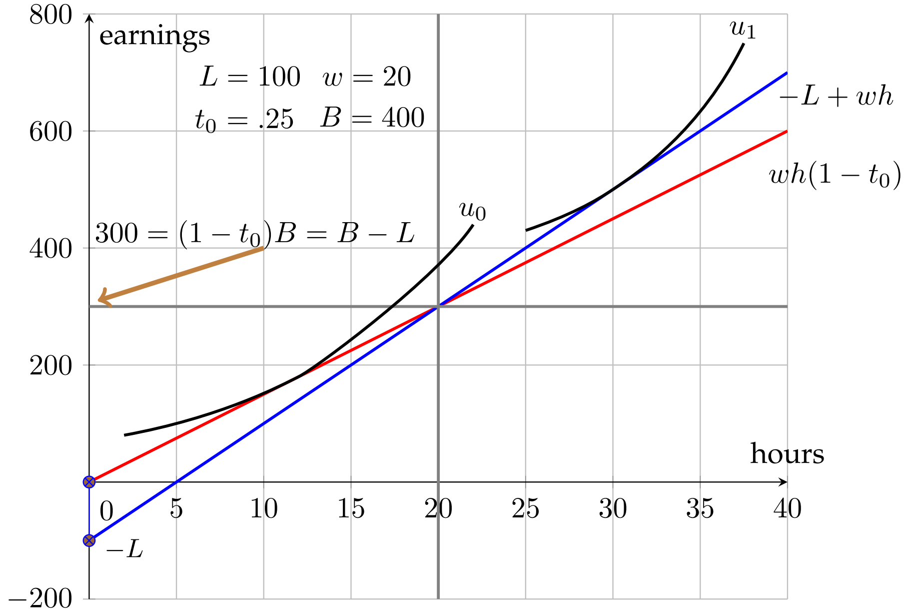


Figure 1: Rideshare and Taxi Budget Lines

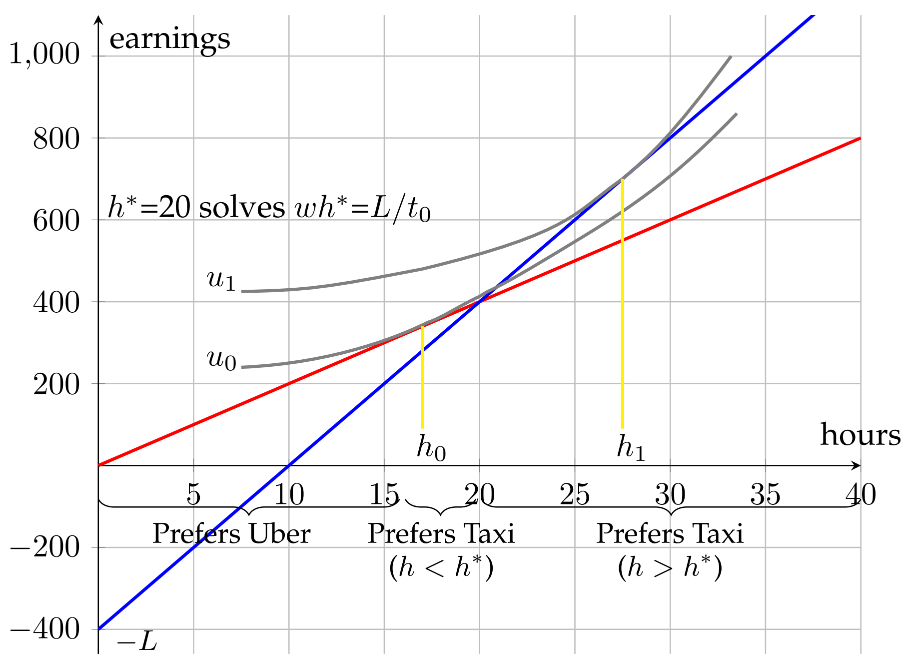


Figure 2: Driven and Elastic Drivers Take Taxi

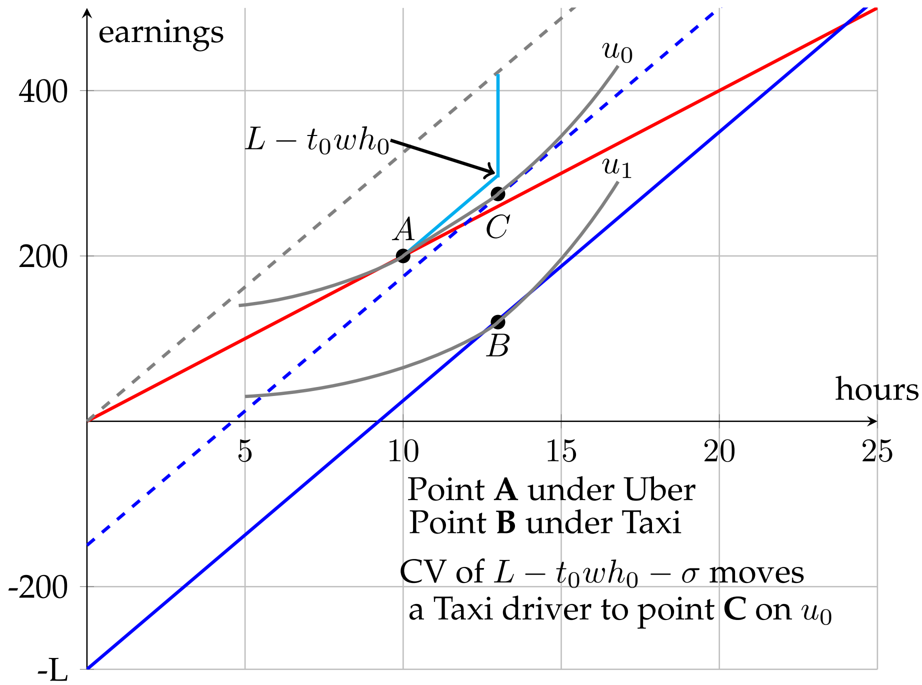


Figure 3: Rideshare vs Taxi Compensating Variation

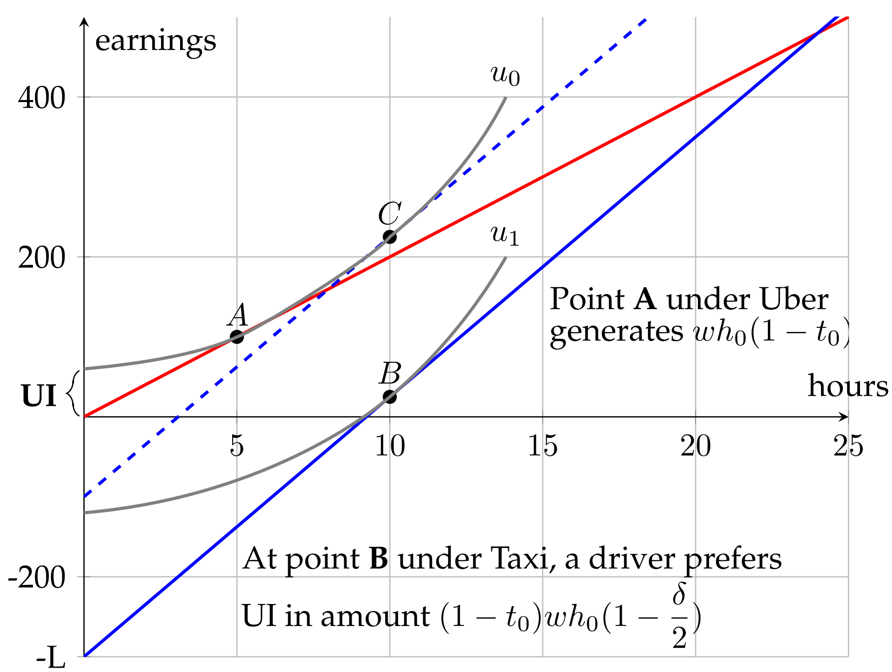
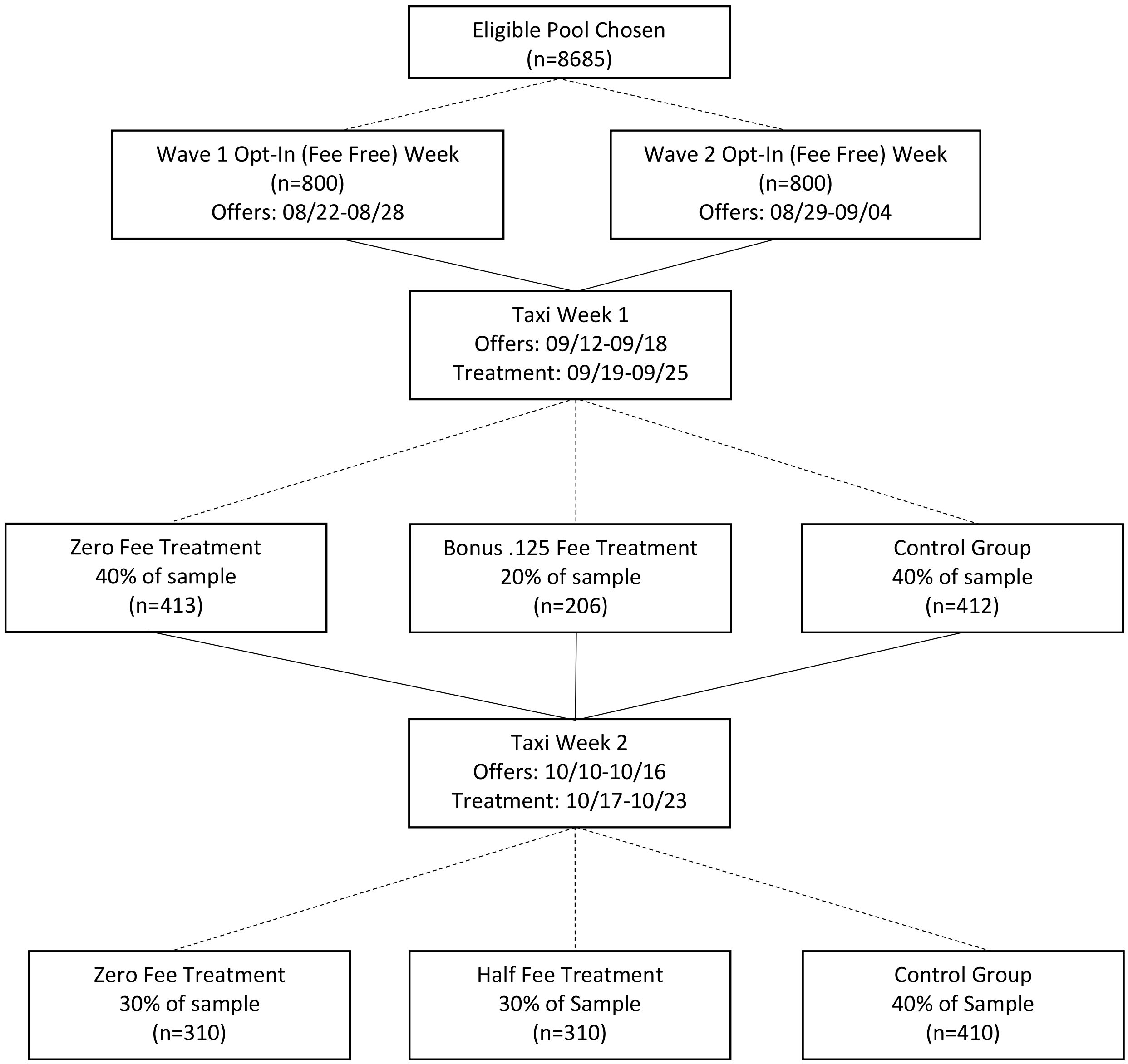


Figure 4: Rideshare vs Taxi Compensating Variation with UI

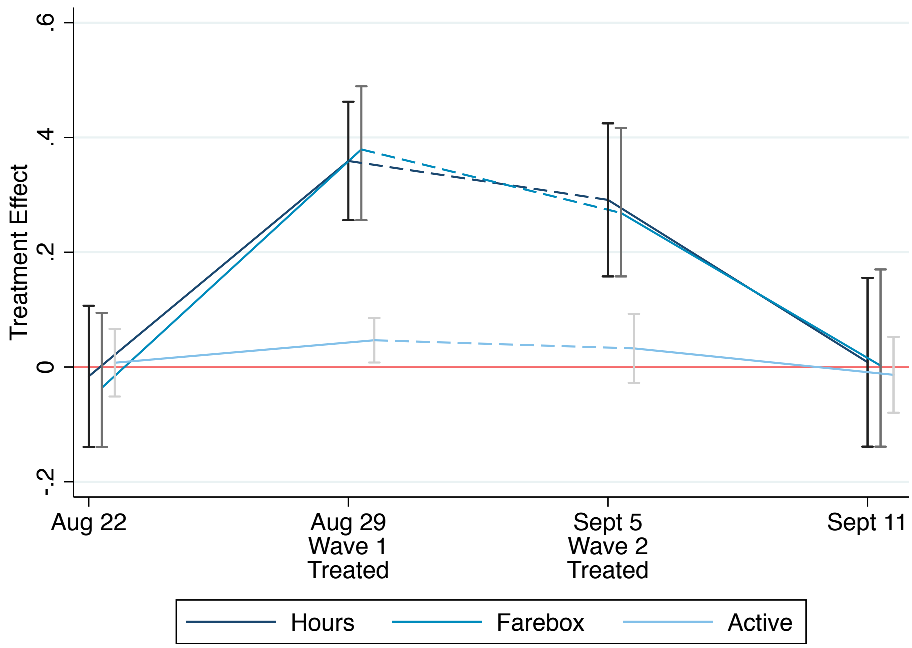
Figure 5: Earnings Accelerator Experimental Design



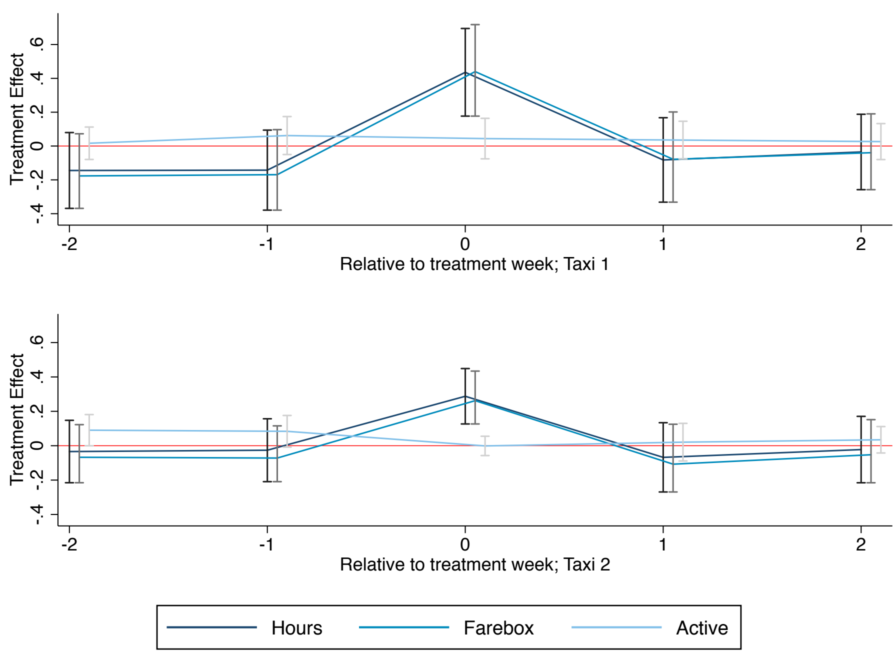
Note: dashed lines denote random assignment.

Figure 6: Participation Effects on Labor Supply

A. Opt-in Week

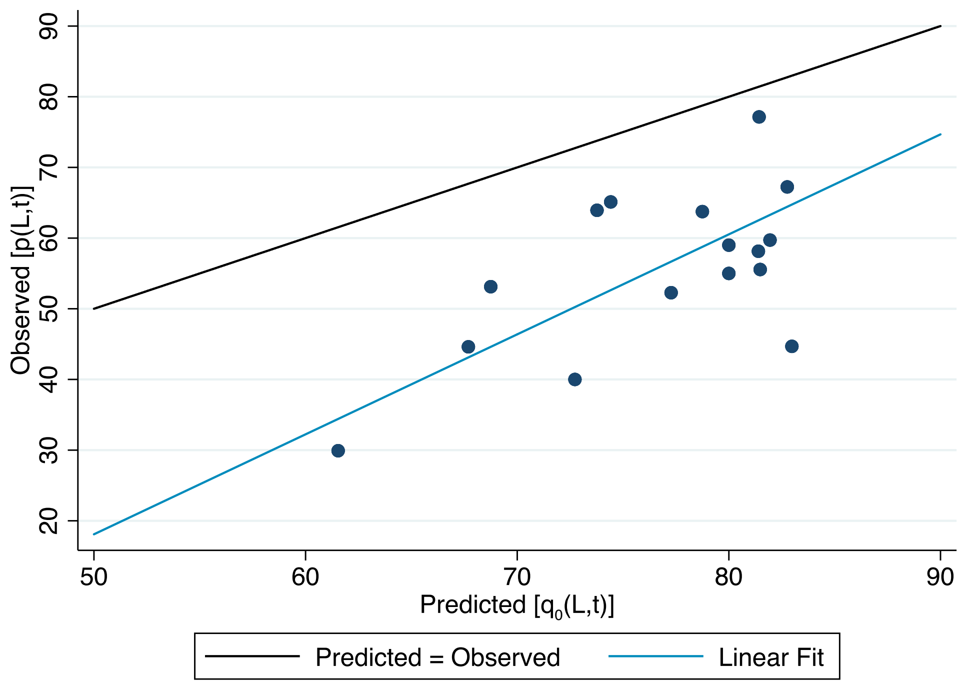


B. Taxi



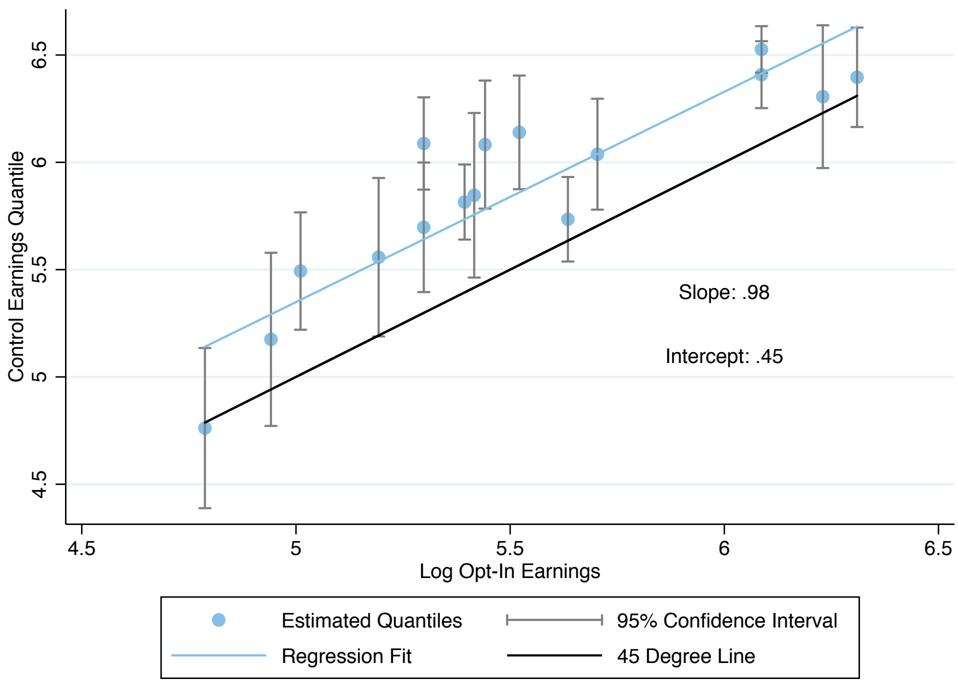
Note: These figures report treatment effects on hours, earnings and an indicator of any Uber activity for drivers who opted in to the Earnings Accelerator. Panel A reports estimates for drivers who accepted the opportunity to drive fee-free. Panel B reports estimates for drivers who bought a Taxi lease. Effects are computed by instrumenting experimental participation with experimental offers as described in the text.

Figure 7: Taxi Under-Subscription



Notes: For each of 16 strata defined by pre-experimental 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. The ISE is set at 1.8. The red indicates the locus of equality for theoretical and empirical take-up. Rates are calculated on the sample of drivers who drove during opt-in week.

Figure 8: 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 opt-in week earnings for the control group against the log of theoretical opt-in earnings, defined as breakeven minus a labor supply adjustment. Quantiles are evaluated using empirical participation rates. Whiskers indicate 95% 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.

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Appendices

Theoretical Appendix

Rideshare Theory with Alternative Jobs

Recapping notation for the alternative job scenario, the cash required to reach utility $\bar{u}$ is:

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

where again it's understood that compensated demands differ under the two compensation schemes. Replicating the proof of the envelope theorem, we write excess expenditure for a Rideshare driver as

$$s^a(w_0, u_0) = px_0 - w_0 h_0 - e(a_0) - \lambda(u(x_0, l_0) - u_0),$$

where λ is the relevant Lagrange multiplier and subscript 0 indicates Rideshare values. Differentiating with respect to after-tax wages, w_0:

$$\begin{aligned}\frac{\partial s^a}{\partial w} &= p\frac{\partial x}{\partial w} - e'(a_0)\frac{\partial a}{\partial w} - h_0 - w_0\frac{\partial h}{\partial w} - \lambda\left[u_x\frac{\partial x}{\partial w} - u_l\left(\frac{\partial a}{\partial w} + \frac{\partial h}{\partial w}\right)\right] \\ &= \frac{\partial x}{\partial w}\left(p - \lambda u_x\right) + \left(\lambda u_l - e'(a_0)\right)\frac{\partial a}{\partial w} - h_0 + \left(\lambda u_l - w_0\right)\frac{\partial h}{\partial w}\end{aligned}$$

where we use the fact that $l = T - (a + h)$ and the derivatives are evaluated at Uber parameters. The dual problem's first-order conditions for an interior solution with Rideshare parameters ensure that $\lambda u_l = w(1-t_0) = w_0$ and $p = \lambda u_x$, so we can simplify:

$$\frac{\partial s^a}{\partial w} = \left(w(1-t_0) - e'(a)\right)\frac{\partial a}{\partial w} - h_0 \tag{21}$$

The scenario we have in mind has positive hours driving for Uber and working on the alternative job, so we also have $w(1-t) = e'(a_0)$. This implies

$$\frac{\partial f^a}{\partial w} = -h_0, \tag{22}$$

as in the model without alternative jobs. Here, however, hours driving differ from total hours worked.

As in the one-job world, Rideshare drivers prefer Taxi when

$$f^a(w, u_0; 0, L) < f^a(w, u_0; t, 0) = s^a(w[1-t], u_0)$$

Using (22):

$$f^a(w, u_0; 0, L) = s^a(w, u_0) + L \approx s^a(w_0, u_0) + L + \frac{\partial s^a}{\partial w}(tw) + \frac{1}{2}\frac{\partial^2 s^a}{\partial w^2}(tw)^2 \tag{23}$$

$$\begin{aligned} &= L + tw\,(-h_0) + \frac{1}{2}\left(-\frac{\partial h_0}{\partial w}\right)(tw)^2 \\ &= L - twh_0 - \frac{1}{2}\left(\frac{\partial h_0}{\partial w}\frac{(1-t)w}{h_0}\right)\frac{t}{1-t}twh_0, \end{aligned}$$

where derivatives are evaluated at Rideshare parameters, so Shephard's Lemma produces compensated Rideshare labor supply and its derivative. As before, Rideshare drivers are happy to drive Taxi when:

$$wh_0 > \frac{L}{t}\left(1 + \frac{1}{2(1-t)}\tilde{\delta}t\right)^{-1}$$

This looks like (3), but the substitution elasticity here, $\tilde{\delta}$, measures the change in hours driving Rideshare or Taxi, while total labor supply includes hours driving plus hours worked on the alternative job.

Also as before, CV for those who drive Taxi when Rideshare disappears is the difference in the excess expenditure functions evaluated at u_0, the utility obtained when the driver drives for Rideshare:

$$CV = f^a(w, u_0; 0, L) - f^a(w, u_0; t_0, 0)$$

Rearranging (23) yields:

$$CV \approx (L - twh_0) - twh_0\frac{\tilde{\delta}t}{2(1-t)}.$$

This is (4), with $\tilde{\delta}$ replacing δ.

Calibrating Risk Aversion

We calibrate the risk aversion required to justify observed Taxi participation decisions using an argument similar to those in Farber (1978), which estimates the risk aversion implicit in United Mine Worker contracts, and Sydnor (2010), which calibrates the risk aversion required to justify the choice of home insurance deductibles.[22]

We start with approximations for any increasing concave utility function, $u(y)$:

$$E[u(y)] \approx u(E[y]) + \frac{1}{2}u''(E[y])\sigma_y^2$$
$$u(b) \approx u(a) + u'(a)(b-a)$$

Let x denote the Uber farebox and let w denote baseline wealth, assumed to be fixed. Using the first expansion, expected utilities for Taxi and Uber are approximated by

$$E[u(w+x-L)] \approx u(w+E[x]-L) + \frac{1}{2}u''(E[w+x-L])\sigma_x^2 \tag{24}$$
$$E[u(w+[1-t]x] \approx u(w+(1-t)E[x]) + \frac{1}{2}u''(w+(1-t)E[x])(1-t)^2\sigma_x^2 \tag{25}$$

We're interested in the scenario where $E[x] > \frac{L}{t}$ but $E[u(w+(x-L)] < E[u((1-t)x]$, that is, the case where a driver would (in expectation) come out ahead by taking Taxi, but chooses not to do so because Uber has lower expected utility.

We can use the second expansion to approximate utility at mean Taxi earnings around mean Uber utility:

$$u(w+E[x]-L) \approx u(w+(1-t)E[x]) + u'(w+(1-t)E[x])(tE[x]-L)$$

Plugging this into the formulas approximating expected utility under Taxi and Uber, equations (24) and (25), we have:

$$\begin{aligned} E[u(w+x-L) - E[w+u((1-t)x] &\approx u'(w+(1-t)E[x])(tE[x]-L) \\ &\quad + \frac{\sigma_x^2}{2}\{u''(w+E[x-L]) - u''(w+(1-t)E[x])(1-t)^2\} \end{aligned}$$

Since $u' > 0$, the left hand side here is less than zero when

$$(tE[x]-L) + \frac{\sigma_x^2}{2}\left\{\frac{u''(w+E[x]-L)}{u'(w+E[x]-L)}\phi - \frac{u''(w+(1-t)E[x])}{u'(w+(1-t)E[x])}(1-t)^2\right\} < 0$$

where $\phi = \frac{u'(w+E[x]-L)}{u'(w+(1-t)E[x])} < 1$, since in the scenario of interest, $u'(w+(1-t)E[x]) > u'(w+E[x]-L)$ as we're above breakeven and marginal utility is diminishing. Therefore,

$$\frac{2(tE[x]-L)}{\sigma_x^2} < r[\phi - (1-t)^2]$$

[22]Sydnor (2010) uses simulation to this end; as in Cohen and Einav (2007), our calibration uses a second-order expansion.

where r is the CARA risk aversion parameter. Note that we require $\phi > (1-t)^2$ for this to hold. Equivalently, therefore,

$$r > \frac{2(tE[x] - L)}{\sigma_x^2[\phi - (1-t)^2]}$$

To translate this into a bound on ρ, the coefficient of relative risk aversion, multiply both sides by $E[x(1-t)+w]$, expected wealth in the Uber scenario:

$$rE[w + x(1-t)] = \rho > \frac{2E[w + x(1-t)](tE[x] - L)}{\sigma_x^2[\phi - (1-t)^2]}$$

Finally, note that since we're fixing baseline wealth (this is usually understood to be permanent income), the relevant variance here is just the variance of the Uber farebox.

To bound ρ we use data on weekly fareboxes for 8 weeks in July and August 2016. We first calculate driver-specific farebox means ($E[x]$) and variances (σ_x^2) using these eight weeks of labor supply data (excluding weeks where a driver chose not to drive). We then calculate an individual-specific bound on ρ for all drivers who *should* have accepted a Taxi contract (on the basis of their prior farebox) but chose not to. Setting $\phi \approx 1$ provides an conservative lower bound on ρ.

The table below shows the results of this calibration for different levels of wealth. Specifically, the table shows the average and quartiles of the distribution of calibrated driver-specific ρ. With even low levels of wealth ($5,000), the median driver (among those who would have benefitted from taxi) would have to have a coefficient of risk aversion near 20 in order to rationalize the observed take-up decisions. Note that w denotes *lifetime* wealth.[23]

Loss Aversion Around a Rideshare Reference Point

Suppose as in Fehr and Goette (2007) that drivers have a linear utility function with a kink at reference point c:

$$u(x-r) = \begin{cases} \lambda(x-c) & x \geq c \\ \gamma\lambda(x-c) & x < c, \end{cases} \tag{26}$$

where $\gamma > 1$ is a coefficient of loss aversion and c is the reference point. In particular, drivers are averse to a scenario where Taxi reduces earnings relative to their Rideshare counterfactual.

We simplify further by assuming wages can take on one of two values, w^H, w^L with probabilities $[p, 1-p]$, while labor supply is fixed at $\bar{h}$, so the only choice is whether to drive

[23]Drivers in our sample also likely have current wealth above $5000. The median driver in our sample has a vehicle that was only four years old when we conducted these experiments.

	Bounds on Risk Aversion			
			Quantile	
	Mean	25th	50th	75th
Wealth	(1)	(2)	(3)	(4)
\$0	8.93	0.41	0.97	2.31
\$500	22.08	1.21	2.87	6.50
\$5,000	140.48	8.04	19.92	44.56
\$10,000	272.04	15.83	39.43	87.35
\$20,000	535.14	31.32	78.44	172.48
\$50,000	1324.47	77.71	195.47	428.33
\$100,000	2640.02	155.02	390.52	854.74

Rideshare or Taxi. The farebox is therefore $W^H = w^h\bar{h}$ and $W^L = w^L\bar{h}$. Drivers want to avoid money-losing Taxi contracts, so we imagine that

$$\begin{aligned} W_H(1-t) &< W_H - L \\ W_L(1-t) &> W_L - L. \end{aligned}$$

When wages are high, farebox exceeds Taxi breakeven, but not otherwise.

Taking the reference point to be potential Rideshare earnings, Taxi driver utility in each state is

$$\text{high}: \ \lambda\left[W_H - L - W_H(1-t)\right] \ = \ \lambda\left[tW_H - L\right]$$

$$\text{low}: \ \gamma\lambda\left[W_L - L - W_L(1-t)\right] \ = \ \gamma\lambda\left[tW_L - L\right].$$

Although motivated by a variable reference point of the sort discussed by Andersen et al. (2014) and Koszegi and Rabin (2006), this model implies a fixed kink at the earnings level determined by Taxi breakeven.

A driver accepts Taxi if the expected utility from doing so is positive, that is, if

$$p\lambda[tW_H - L] + (1-p)\gamma\lambda[tW_L - L] > 0, \tag{27}$$

since Rideshare utility is normalized to zero. Without loss aversion (i.e., $\gamma = 1$) this simplifies to

$$E[W] = pW_H + (1-p)W_L > L/t.$$

In other words, without loss aversion, linear utility means that drivers accept a Taxi contract when expected earnings exceed the Taxi breakeven. Writing W_L as a fraction π of L/t, the participation rule with loss-aversion simplifies to:

$$E[W] > \frac{L\left(p + (1-p)[\pi + (1-\pi)\gamma]\right)}{t} = \frac{\kappa L}{t}$$

where $\kappa > 1$. Loss aversion therefore acts like a proportional increase in lease costs.

Because loss averse drivers act as if lease costs are κL, we replace L with κL when computing CV. Our empirical results suggest that $\kappa \approx 1.4$. We can use this estimate to calculate the implied coefficient of loss aversion, γ, since κ is a function of loss aversion and the parameters of the Uber-Taxi gamble. This implies:

$$\gamma = \frac{\kappa - p - \pi(1-p)}{(1-\pi)(1-p)}$$

Averaging across the two weeks of Taxi, the probability a driver offered Taxi earned more than breakeven was approximately 53%; this is an estimate of p. Conditional on being below breakeven, the expected loss was 27% of breakeven. This is an estimate of π. These values suggest a coefficient of loss aversion of approximately

$$\gamma = \frac{1.4 - .53 - .27(1-.53)}{(1-.27)(1-.53)} \approx 2.2$$

Empirical Appendix (for online publication)

Randomization Balance

The two Taxi experiments offered contracts to the 1031 drivers who opted in to fee-free driving. One of these drivers left Boston between the first and second Taxi weeks and is therefore omitted from week 2 data. The Taxi experiment randomized offers within the four strata defined by previous hours and fee class. Columns 4 and 5 of tables A3 and A4 show that, conditional on strata, drivers are balanced across Taxi treatments and the control group.

Estimates Without Covariates

Table A7 presents estimates of the ISE from models of the form

$$\log h_{it} = \alpha \log w_{it} + \beta X_{it} + \eta_{it} \tag{28}$$

$$\log w_{it} = \gamma Z_{it} + \lambda X_{it} + \upsilon_{it} \tag{29}$$

where X_{it} includes only dummies for randomization strata. These results are qualitatively similar to the results presented in section 4.2, but the model without covariates produces a wider range of estimates: the over-identified models produce estimates ranging from 1.06 to 1.73 (versus 1.09 to 1.4). Results without covariates are also somewhat less precise.

Effects on the Distribution of Hours

Earnings Accelerator participation shifted the entire distribution of hours that treated drivers spent driving. This is clear from Figure A, which plots estimated cumulative distribution functions (CDFs) for participating drivers' potential hours driven during opt-in week and the Taxi trial. The distribution of potential hours for treated drivers in the treated condition can be written $P[h_{1it} < \nu | D_{it} = 1]$, for a constant ν in the support of the hours distribution. This is an observed quantity. But potential hours for treated drivers in an untreated state, written $P[h_{0it} < \nu | D_{it} = 1]$, are counterfactual. Potential hours distributions are estimated using the methods introduced by Abadie (2002; 2003). Specifically, we estimate models of the following form:

$$\begin{aligned} 1[h_{it} < \upsilon](1 - D_{it}) &= X_i'\beta_0(\upsilon) + \alpha_0(\upsilon)(1 - D_{it}) + u_{0i\upsilon} \\ 1[h_{it} < \upsilon]D_i &= X_i'\beta_1(\upsilon) + \alpha_1(\upsilon)D_{it} + u_{1i\upsilon}, \end{aligned}$$

for values of υ between 0 and 80, where D_{it} is instrumented with offers, Z_{it}. The parameters $\alpha_0(\upsilon)$ and $\alpha_1(\upsilon)$ can be shown to describe the CDFs of potential hours for the population of participating drivers, that is, $P[h_{0it} < \nu | D_{it} = 1]$ and $P[h_{1it} < \nu | D_{it} = 1]$.[24]

Figure A suggests that the distribution of hours worked among participating drivers first order stochastically dominates their no-participation counterfactual in each of the four weeks in which fees were reduced. Kolmogorov-Smirnov tests reject the null hypothesis of

[24] Although $P[h_{1it} < \nu | D_{it} = 1]$ is directly observable, we use the same estimating framework for both h_{1it} and h_{0it} to ensure consistent control for covariates.

distributional equality between treated and untreated compliers with p-values of .02 or less. Stochastic dominance of this sort weighs against the hypothesis that target earning behavior causes a substantial number of drivers to reduce their hours worked.

Platform Substitution

Our experimental estimates of the intertemporal substitution elasticity may reflect substitution between jobs. A likely substitution opportunity for Uber drivers is driving for Lyft. We assess the relevance of Lyft substitution for labor supply estimates by estimating the ISE for drivers whose car is too old for Lyft or for whom Lyft is likely to be less attractive than Uber. Those with cars from 2003 or earlier are ineligible to work for Lyft while those with cars from 2010 or older are ineligible for key Lyft promotions. The categorical no-Lyft sample is small and was sampled only during Wave 1 of opt-in week. Our investigation of Lyft substitution therefore combines two empirical strategies, one using random assignment to reduced fees and one using a differences-in-differences (DD) approach.

Columns 1-2 of appendix Table A9 report estimates of the ISE computed using randomized assignment to Taxi treatments in the Lyft-ineligible and Lyft-limited groups. In the Taxi experiment, older-car drivers were randomly assigned to treatment or control on the basis of their hours stratum and fee class without further stratification. The estimated ISEs here range from about .9 to 1.3, not very different from those in Table 5, though considerably less precise. Columns 3-4 report the results of adding data on drivers of older cars during the first opt-in week. This enlarged sample increases precision considerably and produces a pair of estimates in line with those in Table 5.

Our DD strategy combines data from Wave 1 of opt-in week and the week prior to opt-in week, pooling all Wave 2 drivers with the subset of Wave 1 drivers who drive an old car. Wave 2 drivers provide an opt-in week control group for the Lyft-ineligible/limited subset of Wave 1, while the week prior to opt-in week captures any time-invariant differences between Lyft-ineligible/limited drivers and a random sample. In particular, the DD strategy uses this sample to estimate a model that can be written

$$\begin{aligned}\ln h_{it} &= \delta \ln w_{it} + \beta_0 live_t + \beta_1 d_i + \epsilon_{it} \\ \ln w_{it} &= \phi(d_i * live_t) + \alpha_0 live_t + \alpha_1 d_i + \eta_{it},\end{aligned}$$

where the variable $live_t$ indicates data from the first opt-in week when Wave 1 drivers drove fee-free and d_i indicates Wave 1 drivers. The parameter ϕ is the DD estimate of the first stage effect of being a Wave 1 driver during opt-in week. Columns 5 of Table A9 reports the resulting 2SLS estimate of δ pooling hours groups. At 1.32, this estimate is also similar to the ISE estimates reported in Table 5, though again not as precise.

Standard Errors for Participation Analysis

Bootstrap standard errors for the estimates reported in Tables 7 were computed as follows:

1. Draw bootstrap samples of treated and control drivers, stratifying on commission, fee class, and week.

2. Use the control drivers to fit models of the form

$$E[\ln y_{0i}|L_i, t_i, X_i] = E[\ln wh_0|L_i, t_i, X_i] = X_i'\beta$$

   where X_i includes the sets of covariates discussed in the text.

3. Construct the regressor

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

   for treated drivers using $\hat{\beta}$ calculated in step 2, and an intertemporal substitution elasticity of 1.2. Recall that $\sigma(t_i)$ is the proportional participation threshold reduction due to higher Taxi wages.

4. Estimate a Probit model for Taxi participation decisions in the treated sample as a function of $\hat{w}_i$ and a constant

5. The bootstrap standard error is the standard deviation of the estimates of the parameters of interest in 500 bootstrap replications

A Figures and Tables

Figure A1: Taxi Messaging

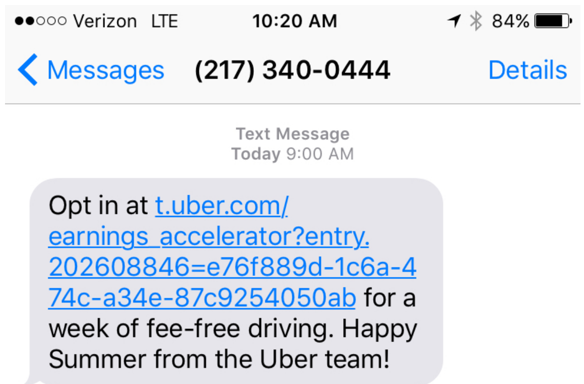


Figure A2: Taxi Slider

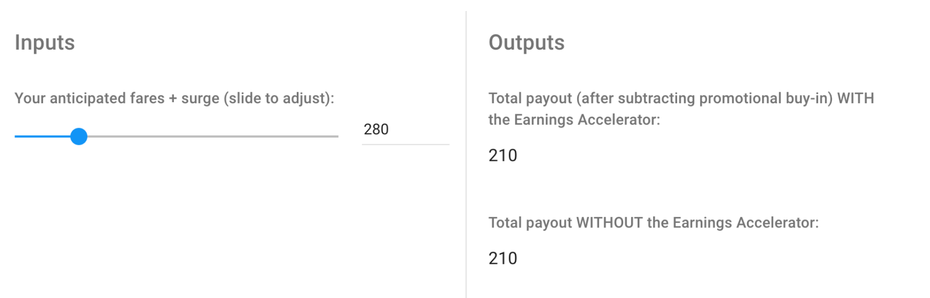
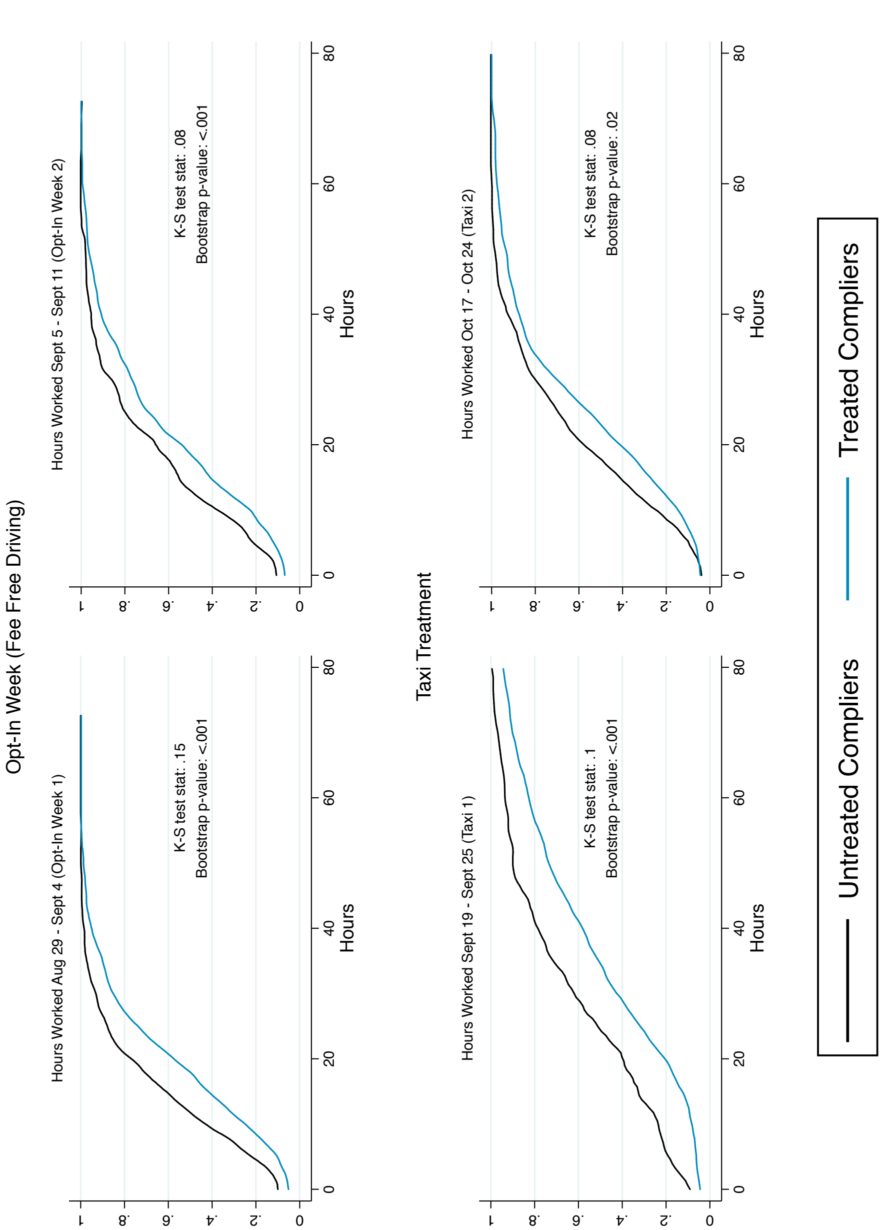


Figure A3: Distribution Treatment Effects



Notes: These figures report estimated CDFs of potential hours driven in treated and non-treated states for drivers who participated in the Earnings Accelerator. Top panels show estimates for drivers who accepted the opportunity to drive fee-free during the opt-in week. Bottom panels show estimates for drivers who bought a Taxi lease. CDFs are estimated by instrumenting participation with experimental offers as described in the text, using a grid of 200 points. CDFS are smoothed using a 5 point moving average.

Table A1: Experimental Timeline

Week Beginning	Action
August 22	Wave 1 Notifications and Opt-In
August 29	Wave 1 Opt-Ins Drive Fee-Free; Wave 2 Notifications and Opt-In
September 5	Wave 2 Opt-Ins Drive Fee-Free
September 12	Taxi 1 Offers and Opt-In
September 19	Taxi 1 Live
September 26	
October 3	
October 10	Taxi 2 Offers and Opt-In
October 17	Taxi 2 Live

Note: This table shows the timeline of the Earnings Accelerator Experiment.

Table A2: Covariate Balance for Wave 1 and Wave 2

	Wave 1 Mean (1)	Strata-Adjusted Difference (2)
Female	0.14	0.02
		(0.02)
Hours the Week Before Selection	16.23	-0.66
		(0.60)
Average Hours/Week the Month Before Selection	14.56	-0.06
		(0.31)
Average Earnings/Hour the Week Before Selection	17.64	-0.38
		(0.43)
Average Earnings/Hour the Month Before Selection	17.14	0.27
		(0.32)
Months Since Signup	10.70	0.01
		(0.25)
Vehicle Solutions	0.07	0.00
		(0.02)
F-statistic		0.79
p-value		0.59
Number of Observations	800	1600

Note: Column 1 reports covariate means for drivers offered fee-free driving in the first opt-in week. Column 2 reports the strata-adjusted difference in means between drivers offered fee-free driving in week 1 and week 2. Robust standard errors are reported in parentheses. Earnings are net of the Uber fee.

Table A3: Covariate Balance for Taxi 1

	Control Mean (1)	T=0 Treated Mean (2)	T=.125 Treated Mean (3)	T=0-Control Difference (4)	T=125-Control Difference (5)
Female	0.16	0.16	0.14	0.00	-0.02
	[0.37]	[0.36]	[0.34]	(0.03)	(0.03)
Hours Last Week of July	16.66	16.01	16.78	-0.67	0.09
	[11.71]	[10.71]	[11.60]	(0.70)	(0.89)
Average Hours/Week in July	14.53	14.81	14.80	0.27	0.25
	[5.66]	[5.71]	[5.69]	(0.20)	(0.24)
Average Hourly Earnings Last Week of July	18.31	18.41	18.53	0.10	0.22
	[8.08]	[7.98]	[8.31]	(0.54)	(0.69)
Average Hourly Earnings in July	17.86	18.40	17.82	0.54	-0.05
	[6.16]	[6.01]	[6.69]	(0.40)	(0.53)
Months Since Signup	11.05	10.82	10.67	-0.21	-0.34
	[8.61]	[8.24]	[8.58]	(0.32)	(0.41)
Vehicle Solutions	0.08	0.10	0.10	0.03	0.02
	[0.27]	[0.31]	[0.30]	(0.02)	(0.02)
Farebox Week Starting 08/22	348.28	356.50	347.56	8.08	-1.20
	[309.29]	[312.33]	[308.88]	(21.04)	(25.05)
Hours Worked Week Starting 08/22	15.31	15.15	15.54	-0.17	0.21
	[13.13]	[12.69]	[13.70]	(0.87)	(1.10)
Car Model Year 2003 or Older	0.11	0.13	0.12	0.02	0.01
	[0.32]	[0.34]	[0.33]	(0.02)	(0.03)
Car Model Year 2011 or Newer	0.58	0.57	0.55	-0.01	-0.03
	[0.49]	[0.50]	[0.50]	(0.03)	(0.04)
F-statistic				0.94*	0.54
p-value				0.50	0.88
Number of Observations	412	413	206	825	618

Note: The 1031 drivers who opted in were randomly assigned within 4 strata defined by hours (high/low) and commission (20/25% commission). Columns 1-3 report sample means for the control group and the two treatment groups. Columns 4 and 5 report the strata-adjusted difference between the means in each treatment group and the control group. Robust standard errors are reported in parentheses. Average hourly earnings include surge but are net of fee. Vehicle solutions drivers lease a car through an Uber-sponsored leasing program.

Table A4: Covariate Balance for Taxi 2

	Control Mean	T=0 Treated Mean	Half Fee Treated Mean	T=0-Control Difference	Half Fee-Control Difference
	(1)	(2)	(3)	(4)	(5)
Female	0.15	0.15	0.17	0.00	0.02
	[0.35]	[0.36]	[0.38]	(0.03)	(0.03)
Hours Last Week of July	16.41	16.43	16.40	0.03	0.01
	[11.35]	[11.30]	[11.25]	(0.76)	(0.76)
Average Hours/Week in July	14.76	14.59	14.73	-0.16	-0.02
	[5.65]	[5.75]	[5.69]	(0.21)	(0.22)
Average Hourly Earnings Last Week of July	18.90	18.15	17.97	-0.74	-0.91
	[8.62]	[7.83]	[7.58]	(0.60)	(0.59)
Average Hourly Earnings in July	18.22	17.93	18.04	-0.27	-0.16
	[6.70]	[5.94]	[5.80]	(0.44)	(0.44)
Months Since Signup	11.15	10.53	10.88	-0.56*	-0.21
	[8.53]	[7.94]	[8.86]	(0.34)	(0.36)
Vehicle Solutions	0.08	0.10	0.10	0.01	0.02
	[0.28]	[0.30]	[0.30]	(0.02)	(0.02)
Farebox Week Starting 08/22	380.58	359.39	394.38	-20.44	14.44
	[393.89]	[399.69]	[387.86]	(28.67)	(28.63)
Hours Worked Week Starting 08/22	12.94	12.52	14.09	-0.40	1.17
	[12.95]	[13.50]	[13.45]	(0.97)	(0.97)
Car Model Year 2003 or Older	0.12	0.13	0.12	0.01	0.01
	[0.32]	[0.34]	[0.33]	(0.02)	(0.02)
Car Model Year 2011 or Newer	0.59	0.55	0.55	-0.04	-0.04
	[0.49]	[0.50]	[0.50]	(0.04)	(0.04)
Treated During Week 1	0.59	0.63	0.59	0.04	0.00
	[0.49]	[0.48]	[0.49]	0.04	0.04
F-statistic				0.76	1.26
p-value				0.69	0.24
Number of Observations	410	310	310	720	720

Note: All but one of the 1031 drivers who accepted the opt-in week promotion were randomly assigned within the 4 strata defined by hours (high/low) and commission (20/25%). The excluded driver left Boston. Columns 1-3 report sample means for the control group and the two treatment groups. Columns 4 and 5 report the strata-adjusted difference between the means in each treatment group and the control group. Robust standard errors are reported in parentheses. Average hourly earnings include surge but are net of fee. Vehicle solutions drivers lease a car through an Uber-sponsored leasing program.

Table A5: Participation 2SLS, Additional Labor Supply Estimates

	Opt-In Week						Taxi					
	Pooled		High Hours		Low Hours		Pooled		High Hours		Low Hours	
	Control Mean	Treatment Effect	Control Mean	Treatment Effect	Control Mean	Treatment Effect	Control Mean	Treatment Effect	Control Mean	Treatment Effect	Control Mean	Treatment Effect
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)
A. Strata Only												
Active (wh>0)	0.78	0.04***	0.85	0.03**	0.70	0.04*	0.75	0.05	0.79	-0.02	0.71	0.12**
		(0.01)		(0.02)		(0.02)		(0.04)		(0.06)		(0.06)
		3200		1600		1600		2062		1058		1004
Log Hours	2.69	0.32***	2.89	0.32***	2.45	0.33***	2.69	0.32***	2.82	0.42***	2.54	0.22**
		(0.03)		(0.04)		(0.05)		(0.08)		(0.11)		(0.11)
		2485		1367		1118		1545		836		709
Log Earnings	5.86	0.34***	6.07	0.32***	5.61	0.37***	5.96	0.28***	6.08	0.37***	5.81	0.19
		(0.04)		(0.05)		(0.06)		(0.09)		(0.13)		(0.12)
		2485		1367		1118		1545		836		709
B. Strata and Covariates												
Active (wh>0)	0.78	0.04***	0.85	0.03**	0.70	0.04*	0.75	0.01	0.79	-0.05	0.71	0.06*
		(0.01)		(0.02)		(0.02)		(0.02)		(0.03)		(0.03)
		3200		1600		1600		1561		840		721
Log Hours	2.69	0.34***	2.89	0.33***	2.45	0.35***	2.69	0.39***	2.82	0.40***	2.54	0.34***
		(0.03)		(0.04)		(0.05)		(0.07)		(0.09)		(0.09)
		2485		1367		1118		1422		775		647
Log Earnings	5.86	0.36***	6.07	0.34***	5.61	0.39***	5.96	0.36***	6.08	0.36***	5.81	0.32***
		(0.04)		(0.05)		(0.06)		(0.07)		(0.10)		(0.10)
		2485		1367		1118		1422		775		647

Note: This table reports 2SLS estimates of effects on labor supply. The endogenous variable is participation, instrumented with treatment offers. Models controls for the strata used for random assignment and for time dummies. Models with covariates contain additional controls for gender, months driving for Uber, car age (2003 or newer), and one lag of log earnings. Standard errors are clustered by driver. The number of observations contributing to each estimate appears beneath the standard error.

Table A6: Participation 2SLS, Estimates for Other Outcomes

	Opt-In Week						Taxi					
	Pooled		High Hours		Low Hours		Pooled		High Hours		Low Hours	
	Control Mean	Treatment Effect	Control Mean	Treatment Effect	Control Mean	Treatment Effect	Control Mean	Treatment Effect	Control Mean	Treatment Effect	Control Mean	Treatment Effect
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)
Completed Trips	33.40	12.48***	42.27	14.38***	24.54	10.48***	34.51	11.92***	39.91	14.22***	28.83	9.84**
		(1.00)		(1.50)		(1.30)		(3.14)		(4.95)		(3.85)
		3200		1600		1600		2062		1058		1004
Number of Days Worked	3.68	0.69***	4.34	0.64***	3.03	0.74***	3.56	0.72***	3.88	0.72**	3.23	0.74**
		(0.08)		(0.11)		(0.12)		(0.25)		(0.37)		(0.32)
		3200		1600		1600		2062		1058		1004
Hourly Farebox	24.73	0.33	24.78	-0.20	24.67	0.95**	27.44	-0.72	27.54	-1.20	27.33	-0.42
		(0.25)		(0.28)		(0.42)		(0.71)		(1.07)		(0.92)
		2485		1367		1118		1545		836		709
Proportion Trips on Surge	0.18	-0.01	0.18	-0.01	0.18	0.00	0.26	-0.01	0.26	0.00	0.26	-0.03
		(0.01)		(0.01)		(0.01)		(0.02)		(0.03)		(0.02)
		2485		1367		1118		1545		836		709
Average Rating	4.78	-0.01	4.79	-0.01	4.78	-0.01	4.80	-0.01	4.81	-0.01	4.80	-0.01
		(0.01)		(0.01)		(0.02)		(0.02)		(0.03)		(0.03)
		2474		1362		1112		1537		832		705
Proportion Rated	0.79	0.00	0.78	0.00	0.79	0.00	0.78	0.00	0.78	0.01	0.79	0.00
		(0.01)		(0.01)		(0.01)		(0.01)		(0.01)		(0.01)
		2474		1362		1112		1537		832		705

Note: This table reports 2SLS estimates of effects on other outcomes. The endogenous variable is participation in fee-free driving or Taxi, instrumented with treatment offers. Models controls for the strata used for random assignment and for time dummies. Models with covariates contain additional controls for gender, months driving for Uber, car age (2003 or newer), and one lag of log earnings. Standard errors are clustered by driver. The number of observations in each regression appears beneath the standard error.

Table A7: ISE Estimates from Models Without Covariates

	Opt-In Week			Taxi		
	Pooled	High Hours	Low Hours	Pooled	High Hours	Low Hours
	(1)	(2)	(3)	(4)	(5)	(6)
			A. 2SLS Estimates			
First Stage	0.20***	0.19***	0.22***	0.11***	0.10***	0.13***
	(0.01)	(0.01)	(0.02)	(0.02)	(0.03)	(0.03)
2SLS	1.13***	1.20***	1.06***	1.68***	2.22***	1.14**
	(0.12)	(0.17)	(0.18)	(0.46)	(0.76)	(0.58)
Over-identified	1.16***	1.22***	1.10***	1.39***	1.73***	1.06**
Model	(0.12)	(0.17)	(0.18)	(0.29)	(0.41)	(0.42)
			B. OLS Estimates			
OLS	0.37***	0.37***	0.36***	0.38***	0.33***	0.45***
	(0.06)	(0.09)	(0.09)	(0.09)	(0.10)	(0.15)
Drivers	1344	721	623	864	462	402
Observations	2485	1367	1118	1544	836	708

Note: This table reports 2SLS estimates of the ISE. The endogenous variable is log wages, instrumented with treatment offers. The over-identified model in columns 1-3 uses separate treatment indicators for each week, fee class, and hours group. The over-identified model in columns 4-6 uses separate treatment indicators for each taxi offer. Models control for the strata used for random assignment and time dummies. Standard errors are clustered by driver. A total of 1600 drivers were offered fee-free driving in opt-in week; 1031 accepted the offer and were eligible for Taxi leasing. Sample sizes in columns 1 and 4 are lower because the data used to construct this table omit zeros.

Table A8: Compensating Variation with UI

	Weekly Lease Rates						
	$50	$100	$150	$200	$400	$600	$800
Wage Gap	(1)	(2)	(3)	(4)	(5)	(6)	(7)
	A. Nominal Lease						
	-$44	-$5	$27	$53	$124	$159	$175
15%	17%	31%	43%	53%	77%	89%	96%
	-2.4%	-8%	-14%	-21%	-51%	-73%	-87%
	-$78	-$39	-$6	$23	$99	$139	$159
20%	15%	29%	41%	50%	75%	87%	94%
	-2.1%	-6.7%	-13%	-19%	-47%	-69%	-84%
	-$116	-$75	-$41	-$12	$71	$117	$142
25%	14%	28%	39%	48%	72%	85%	93%
	-1.9%	-6.0%	-11%	-17%	-43%	-65%	-80%
	-$385	-$341	-$301	-$264	-$147	-$65	-$7
50%	8%	18%	27%	34%	56%	71%	80%
	-1%	-2.8%	-6%	-9%	-25%	-41%	-56%
	B. Behavioral Lease						
	-$27	$21	$58	$88	$154	$177	$183
15%	23%	41%	54%	65%	88%	97%	99%
	-4%	-13%	-23%	-33%	-69%	-89%	-97%
	-$61	-$12	$28	$59	$133	$162	$171
20%	21%	39%	52%	62%	86%	95%	98.9%
	-4%	-11%	-21%	-31%	-65%	-86%	-96%
	-$99	-$48	-$6	$27	$110	$145	$158
25%	20%	37%	49%	59%	83%	94%	98.3%
	-3.3%	-10%	-19%	-28%	-61%	-83%	-94%
	-$367	-$308	-$257	-$212	-$79	$3	$52
50%	13%	25%	35%	44%	68%	82%	90%
	-1.6%	-5%	-9%	-15%	-38%	-58%	-74%

Notes: Panel A shows compensating variation (CV, paid to Rideshare drivers to induce them to work under Taxi), computed for the nominal lease rates listed in columns 1-7. Panel B evaluates CV using behavioral lease rates computed from Taxi take-up. The behavioral lease is fifty 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 reports the percent of drivers on UI and the third reports the percent change in aggregate hours supplied, relative to a scenario without UI. CV is evaluated using weekly earnings and hours data for all Boston Uber drivers who completed at least 4 trips in July 2016. Weeks with zero trips are omitted. The mean farebox conditional on driving is 541. The mean payout conditional on driving is 423.

Table A9: No-Lyft and Low-Lyft Uber ISEs

	Random Assignment				DD
	Taxi		Taxi + Wave 1		(Opt-in Waves)
	2003-	2010-	2003-	2010-	2003-
	(1)	(2)	(3)	(4)	(5)
First Stage	0.11**	0.11***	0.13***	0.17***	0.23***
	(0.05)	(0.03)	(0.04)	(0.02)	(0.03)
2SLS	0.88	1.30*	1.36***	1.38***	1.32***
	(1.20)	(0.68)	(0.47)	(0.23)	(0.37)
OLS	0.23	0.14	0.46***	0.36***	0.08
	(0.23)	(0.14)	(0.14)	(0.07)	(0.09)
Number of Observations	101	363	150	533	839
Number of Drivers	174	633	294	1060	1538

Note: This table reports 2SLS estimates of the ISE for drivers with cars older than 2003 and 2010. The first group cannot drive for Lyft; the second receives limited Lyft promotions. The row labeled OLS reports estimates from a regression of log hours on log wages. The row labeled 2SLS reports IV estimates generated by instrumenting wages. ISE estimates in columns 1-4 use random assignment of older-car drivers during Taxi weeks and the first opt-in week. Column 5 reports difference-in-differences estimates of the ISE using data from the first opt-in week and the week priors, pooling all Wave 2 drivers with the subset of Wave 1 drivers who drive an old car, and instrumenting with a dummy for being treated during opt-in week. Standard errors are clustered by driver. All specifications control for hours bandwidth, commission, and time dummies. Columns 1-4 control for one lag of log earnings.