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

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Abstract

Ride-hailing drivers pay a proportion of their fares to the ride-hailing platform operator, a commission-based compensation model used by many internet-mediated 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, but keep every fare dollar net of expenses. We assess these compensation models from a driver's point of view 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. At the same time, our virtual lease program was under-subscribed: many drivers who would have benefitted from buying an inexpensive lease chose to opt out. We use these results to compute the average compensation required to make drivers indifferent between ride-hailing and a traditional taxi compensation contract. The results suggest that ride-hailing 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. Limited supply of taxi medallions has made 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 ride-hailing platforms, including Uber, means that many workers now have the opportunity to add to their earnings by offering hackney services in private vehicles, no medallion lease required. In 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 additional to reducing entry barriers and perhaps taxi fares, an important feature of the ride-hailing model is a proportional compensation scheme, with few or no fixed costs. In return for a percentage of their earnings known to drivers as a fee or commission, ride-hailing 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 work on a ride-hailing platform.[1]

This paper looks at the economic value of ride-hailing work opportunities for drivers, focusing on differences in the compensation arrangements available to traditional taxi and ride-hailing 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-than-Uber taxi wage. The response to our offers reveals a large, precisely estimated intertemporal substitution elasticity for the Uber wage effect on Uber hours, on the order of 1.2. 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

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

targeting as argued in, e.g., Camerer et al. (1997).[2] Our estimated substitition elasticities are also in line with the Mas and Pallais (2017) experimental estimates of compensated elasticities for part-time workers with flexible hours.

The labor supply elasticity is a key parameter in our evaluation of the ride-hailing compensation contract. A large intertemporal substitution elasticity (ISE) tends to make medallion-type contracts more attractive since the medallion system raises wages. 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 (that is, driver surplus lost) when Uber's proportional compensation scheme is replaced by leasing. Even without lease aversion, the opportunity to drive with no lease payment generates surplus for most Uber drivers unless lease prices fall below about \$100 per week. In the face of a \$200 weekly lease, lease aversion increases Boston drivers' average ride-hailing surplus to nearly one-third of average Uber earnings.

This paper focuses on the value of ride-hailing work opportunities for drivers, but our theoretical framework and empirical strategy may be used to assess compensation schemes on other jobs with entry barriers, where the "right to work" can be purchased at either a flat rate or a rate proportional to earnings. Service professionals like hair stylists and cosmetologists face this sort of choice, either working on commission or renting a chair, in which case they're independent contractors keeping what they make. Many franchise contracts make this trade-off explicit: 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.

2 Theoretical Framework

Our experiment is motivated by a stylized contrast between the compensation schemes embedded in ride-hailing and traditional taxi work arrangements. In Boston, until recently,

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

Uber took a flat fee of 20% or 25% of gross fares (referred to here as the Uber "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 offers its drivers the opportunity to rent or lease cars through a program known as "vehicle solutions," though few drivers do this.[3]

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.[4]

2.1 Taking Taxi

We use the term "Taxi" to refer to hackney carriage jobs characterized by the compensation schemes offered to Uber drivers in our experiment. Fares are cast in terms of average hourly earnings, w, taken to be the same for Uber and Taxi drivers. This is unrestrictive because differences in wages can be modeled as part of the Uber fee, or reflected in a negative fee for Taxi drivers.

[3] 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 ride-share operator requires drivers to make advance payments analogous to medallion leasing.

[4] 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).

Drivers drive for h hours, so their weekly farebox is wh. Driver compensation schemes can be described using this notation as follows:

1. Uber drivers earn $y_0 = w(1 - t_0)h$, where t_0 is the Uber fee.

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

Drivers can choose not to work and earn 0 dollars, but leases must be purchased in advance. The quantity $t_0 - t_1$ is the difference in "tax rates" implicit in the two contracts.

Our analysis takes the wage rate, w, as given. Of course, the entry of thousands of new drivers into the Boston cab market might change the equilibrium wage. Uber has almost certainly reduced the traditional taxi farebox, a fact reflected in steeply falling medallion prices. The effect on driver earnings is less clear, however, since rents generated by the traditional system may be retained by medallion owners rather than distributed to drivers. Competitive ride-hailing employment opportunities might therefore boost pay for some workers in the hackney carriage sector. A differences-in-differences-style analysis of Uber entry effects on workers classified in the "Taxi Drivers and Chauffeurs" occupation in the American Community Survey suggests Uber reduced the hourly earnings of wage-employed drivers by 8-10%, but this is offset by much larger gains for the self-employed (Berger et al., 2017). Averaging the two groups, driver pay looks to be essentially unchanged.

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 Uber and Taxi week by week. Alternately, we can imagine Taxi as permanently displacing Uber 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 Uber in a life-cycle framework where the opportunity to choose between ride-hailing and Taxi may be transitory and future wages are uncertain.

Figure 1 sketches the Uber 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 Uber fee (these are realistic values for wages and fees, 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 by driving for Uber. 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 Uber, while a driver with indifference curve u_1 prefers Taxi.

Figure 1 compares a pair of drivers with fareboxes above and below breakeven. Drivers above breakeven always benefit from Taxi. Some drivers with below-breakeven farebox under Uber 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 opt-in farebox 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

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

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. Shephard's lemma applied to the excess expenditure function yields $-h^c$, the negative of compensated labor supply.

We model Uber 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 hit $\bar{u}$ 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 for Uber, 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 opt for Taxi when

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

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 Shephard's lemma to expand $s(w, u_0)$ around $s(w_0, u_0)$, the Taxi opt-in rule is

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

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

The opt-in inequality can be rewritten

$$L - \frac{\delta t_0}{2(1-t_0)} t_0 w h_0 < t_0 w h_0, \tag{2}$$

where δ is the substitution elasticity evaluated at the after-fee Uber wage. That is,

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

Finally, it's useful to write the Taxi opt-in rule in terms of of the Taxi breakeven:

$$\underbrace{w h_0}_{\text{Uber farebox}} > \frac{L}{t_0}(1 + \frac{\delta}{2}\frac{t_0}{1-t_0})^{-1}. \tag{3}$$

This shows that a positive substitution elasticity reduces the opt-in threshold by the proportional amount

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

Eligible drivers with an Uber farebox that clears breakeven should always prefer Taxi. But some with a farebox below breakeven should also opt-in. With a unit-elastic compensated response and an Uber fee of 25%, for example, we expect the opt-in farebox to be reduced relative to breakeven by $1 - \frac{1}{1+.25/2\times.75} \approx 14.5\%$.

UI Instead of Taxi

When Taxi is the only option, some Uber drivers may prefer not to drive. We say that these drivers "prefer unemployment insurance (UI) to Taxi." Formally, these drivers have negative consumption when constrained to be on u_1 at zero hours driving. To determine who prefers UI, we assume that drivers who face a wage of zero choose to drive zero hours, so their expenditure, $s(0, u_1)$, is the u_1 ordinate. Note also that $s(w, u_1) + L = f(w, u_1; t = 0, L) = 0$, since no transfer is needed for a lease-paying Taxi driver to obtain u_1. Expanding $s(0, u_1)$ around $s(w, u_1)$ therefore delivers a simple expression (derived in the appendix) for the condition that $s(0, u_1) < 0$:

$$wh_1(1 - \frac{\delta}{2}) < L. \tag{4}$$

Not surprisingly, a driver with Leontief preferences prefers UI to Taxi if his Taxi farebox fails to cover his lease. Drivers with a positive substitution elasticity will trade consumption for leisure, so even when earning enough to cover a lease, some still prefer UI.

2.2 Compensating Taxi

We are interested in the level of compensation required for loss of the opportunity to drive for Uber (evaluated in a sample of current Uber drivers). This is a measure of compensating variation (CV), where the baseline condition is the Uber budget line with an interior solution and the alternative is the Taxi budget set. Positive CV means payment is required for the imposition of Taxi, while negative values arise for drivers who prefer Taxi. Although CV is tied to the specifics of the Taxi compensation scheme on offer, the results of our experimental Taxi-Uber comparisons can be used to extrapolate compensation values to markets with higher lease costs and various Taxi-Uber fare gaps.

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

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

where u_0 is the Uber utility level. The second-order expansion that yields opt-in cut-offs in

Section 2.1 likewise implies

$$f(w, u_0; 0, L) \approx f(w, u_0; t_0, 0) + L - h_0 t_0 w - \frac{1}{2}\frac{\partial h^c}{\partial w}(t_0 w)^2. \tag{5}$$

Subtracting $f(w, u_0; t_0, 0)$ from $f(w, u_0; 0, L)$ or, equivalently, noting that $f(w, u_0; t_0, 0) = 0$, the CV required as compensation for Taxi is seen to be

$$CV = \{L - t_0 w h_0\} - t_0 w h_0 \frac{\delta t_0}{2(1 - t_0)}. \tag{6}$$

This formula mirrors equation (2): Uber drivers for whom CV is negative drive Taxi when it's offered.

A Leontief driver should be paid the difference between his lease costs and his Uber fees. As with our opt-in equation, elastic labor supply favors Taxi, reducing CV. Even so, the principal determinant of CV for most drivers is likely to be $L - t_0 w h_0$. This difference is largest for Uber's low-hours drivers, of which there are many. 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 Uber to Taxi budget lines. An Uber 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 Uber 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* Uber 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 (6) 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 Uber fees, $t_0 w h_0$. This product approximates the area under the driver's supply curve between his after-tax Uber and Taxi wages.

Sitting Out

The compensation formula above presumes Uber drivers accept the Taxi budget line as a condition for compensation. But we might also allow former Uber drivers to refuse Taxi, taking some of their compensation in the form of increased leisure. Drivers who make this choice have an Uber farebox below the UI opt-in defined by equation (4), and so 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 again 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 Uber utility with a wage of zero around Uber expenditure with a fee of t_0, we have:

$$s(0, u_0) = s(w_0, u_0) + (-h_0)(-w(1 - t_0)) - \frac{1}{2}\frac{\partial h^c}{\partial w} w^2(1 - t_0)^2. \tag{7}$$

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

$$UI = (1 - t_0)wh_0 - \frac{1}{2}\left(\frac{\partial h^c}{\partial w}\frac{w(1 - t_0)}{h_0}\right)([1 - t_0]wh_0) \tag{8}$$

$$= (1 - t_0)wh_0\left[1 - \frac{\delta}{2}\right] \tag{9}$$

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

Life-Cycle Considerations

Drivers' hourly wages are uncertain when medallions are leased, so it's worth considering the Uber-Taxi comparison in a multi-period environment. We do this here 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. Frisch labor 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 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 constant r is interpreted as a fixed "price of utility". 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 Uber and Taxi at time (week) s. This driver prefers Taxi if the Taxi contract is profitable for that week. That is, Taxi beats Uber in week s if,

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

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.[5]

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

$$\frac{\partial \pi_s(r, w_s[1 - t_0])}{\partial w} w_s t_0 + \frac{1}{2}\frac{\partial^2 \pi_s(r, w_s[1 - t_0])}{\partial w^2}(w_s t_0)^2 > L. \tag{10}$$

Applying a life-cycle version of Shephard's lemma, this expansion becomes

$$L - t_0 w_s h_{s0} - \frac{1}{2}\frac{\partial h_s^f(r, w_s[1 - t_0])}{\partial w}(w_s t_0)^2 < 0,$$

where $h_{s0} \equiv h_s^f(r, w_s[1 - t_0])$ is Frisch labor supply driving for Uber in period s. The earlier opt-in rule therefore stands, but with the Hicks substitution elasticity replaced by the possibly

[5] 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.

larger ISE, denoted δ^f:

$$\underbrace{w_s h_{s0}}_{\text{Uber earnings}} > \frac{L}{t_0}\left(1 + \frac{\delta^f}{2}\frac{t_0}{(1-t_0)}\right)^{-1}, \tag{11}$$

where $\delta^f \equiv \frac{\partial h_s^f(r,w_s)}{\partial w_s}\frac{w_s(1-t_0)}{h}$.

The revision to CV in a life-cycle framework parallels that for opt-in. 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 (10), this becomes:

$$CV = \{L - t_0 w_s h_{s0}\} - t_0 w_s h_{s0}\frac{\delta^f t_0}{2(1-t_0)}. \tag{12}$$

This is the same as (6), 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 favor Taxi. Because our experimental design offers temporary wage changes, we interpret the experiment as identifying δ^f.

In this life-cycle framework, workers who make consumption and labor supply decision in the face of uncertain wages can be shown to behave according to $h_s^f(r_s, w_s)$, where r_s is a time-varying price of utility that reflects the arrival of new information in period s. New information potentially causes a revision in a driver's marginal utility of wealth. Assuming this information arrives before a prospective Taxi driver must buy a lease, uncertainty has no implications for the Taxi-Uber comparison, since the utility price does not appear in the opt-in inequality.

In practice, drivers must forecast next week's wage (which determines farebox) when considering a weekly lease. Suppose that an Uber driver who doesn't know next week's wages is offered the opportunity to buy a one-week lease. His marginal utility of lifetime wealth presumably changes little either way, but he must predict w. Knowing how much he will drive in response, the wage implies a predicted farebox. Our econometric framework (outlined below) embeds farebox prediction in an empirical model for Taxi participation.

We also consider the possibility that Uber drivers find the risk inherent in this choice unattractive, either because of conventional risk aversion or behavioral loss aversion. Risk aversion comes into play because Taxi contracts increase the variance of wages by $\left[\frac{1}{1-t_0}\right]^2$. Rabin (2000) argues, however, that globally concave utility is unlikely to produce a coherent account of choices over small gambles (Chetty 2006 extends this argument to labor supply). The appendix illustrates this argument for the Taxi-Uber comparison using statistics from our data, which imply that the level of risk aversion required for concavity alone to explain the lease aversion seen in our experiment is implausible.

Although risk aversion resurfaces in the model of consumption commitments proposed by Chetty and Szeidl (2016), our narrative favors a loss aversion story since this leads directly to an estimating equation for behavioral taxi take-up and produces a plausible loss aversion parameter. In any case, we needn't know precisely why Uber drivers find leasing unattractive. Both risk aversion and loss aversion are captured by modeling drivers as behaving as if the lease required for a Taxi contract exceeds the nominal lease. These excess costs then modify the lease values in our CV formula.[6]

2.3 Don't Quit Your Day Job

Many Uber drivers work at another job (Hall and Krueger, 2017). A leading Uber alternative is likely to be driving for another ride-hailing platform such as Lyft. Drivers can move easily between ride-hailing platforms, though not all do so. Lyft almost certainly provides the alternative employment opportunity from which hours are most elastically substituted towards Uber, though other jobs might also allow a transfer of hours. This section briefly explores the theoretical consequences of multiple job-holding for our labor supply and welfare analysis.

In Boston, Uber drivers can typically drive as much as they want at the implicit market wage. The Uber wage may be higher at certain times of day, but Boston Uber drivers do not

[6]The life-cycle framework highlights possible differences between long-run and short-run Uber vs Taxi comparisons. The experimental scenario is a series of one-off weekly decisions, much as the lease decision facing a traditional medallion-leasing taxi driver. Each of these decisions is essentially wealth neutral even in an uncertain world. The labor supply response to higher Taxi wages therefore reflects intertemporal substitution. A life-cycle plan involving "Taxi forever" may have consequences for the marginal utility of wealth, in which case labor supply elasticities should be revised accordingly. On the other hand, many Uber drivers drive for only a few months and only about half are still on the platform a year after activation (Hall and Krueger, 2017). For many drivers, therefore, lifetime wealth effects should play little role in Uber vs Taxi comparisons even in the face of enduring ride-hailing policy or wage changes. We return briefly to this issue in Section 6, below.

usually have to wait long between trips. It therefore seems reasonable to model movement between Uber and alternative jobs 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 Uber drivers earn $e(a)$ for a hours worked on an alternative job, where $e(a)$ is increasing but concave.[7]

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 with driving (Uber or Taxi) wage w and parameters L, t, yields the relevant excess expenditure functions:

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

$$\frac{\partial f^a}{\partial w} = \frac{\partial s^a}{\partial w} = -h^c, \tag{13}$$

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

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

$$wh_0 > \frac{L}{t_0}\left(1 + \frac{1}{2(1-t_0)}\tilde{\delta}t_0\right)^{-1}. \tag{14}$$

[7]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.

This looks like (3), but the substitution elasticity in this case, denoted by $\tilde{\delta}$, measures the change in *hours driving* (Uber or Taxi), 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 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. Such substitution leaves our welfare analysis unchanged, while changing the interpretation of the ISE identified by our experiment.

3 Experimental Design

Uber and its ride-hailing competitors routinely offer drivers temporary increases in pay known to drivers as promotions. Riders are typically unaware of these changes in driver pay. Promotions are used to increase trip supply, equilibrating supply and demand without the need for surge pricing. We identified labor supply elasticities and lease aversion parameters using a randomized experiment pitched to drivers as an Uber promotion called the *Earnings Accelerator*.

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.[8] 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 of the eligible sample.

3.1 Opt-In Weeks

A total of 1600 drivers were selected randomly from the eligible pool. Half (Wave 1) were offered a week of fee-free driving in the first opt-in week. While the first wave was driving fee-free, the second half (Wave 2) was offered the opportunity to opt in for fee-free driving the following week. This design mirrors the bicycle messenger experiment used by Fehr and Goette (2007) to estimate labor supply elasticities. Appendix Table A2 shows that driver characteristics are well balanced across waves. Appendix Table A1 sketches the experimental timeline.

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

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

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 and offers of promotions. Some of this daily barrage of texts, emails, and in-app notifications is likely ignored.[9] Drivers who opted in also gave consent for their data to be used in academic research and consented 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 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.

3.2 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. There were 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

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

week, 40% of drivers in each stratum were 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 during the week of solicitation for fee-free driving, 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.

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 earn 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 once any reduced-fee trip was completed.

4 Labor Supply Effects

Our analysis of the labor supply response to reduced fees uses Uber's data on driver earnings and hours worked to estimate the effects of fee reductions on participating drivers. The hours data measure the time a driver is active on the Uber platform, that is, the time drivers spend online either taking trips, driving to pick up passengers, or waiting for trips. Drivers are discouraged from going or remaining online without accepting trips.

4.1 Participation 2SLS

The fee reductions offered through the Earnings Accelerator were conditional on driver agreement to participate: drivers who failed to opt-in to either fee-free driving or to buy a Taxi lease should have been unaffected by these offers. Program participation is a choice that might be correlated with potential labor supply outcomes, but opportunities to participate were randomly assigned. We therefore use offers as instruments in a two-stage least squares (2SLS) setup that captures the impact of Earnings Accelerator *participation* on labor supply. Because no one not offered a treatment takes it, the 2SLS estimand in this framework is an average causal effect of participation on Earnings Accelerator participants. Formally, let Y_{1it} denote a potential outcome for driver i in week t when participating and let Y_{0it} denote his potential outcome otherwise. The 2SLS estimator using an offer dummy to instrument D_{it} identifies $E[Y_{1it} - Y_{0it}|D_{it} = 1]$, where D_{it} indicates Earnings Accelerator participation (see, e.g., Angrist and Pischke 2009).

The analysis sample for 2SLS estimation of treatment effects on participants stacks data for two pairs of weeks: the first pair contains data on 1600 drivers from the first two waves, during which first one half then the other were offered fee-free driving; 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. For example, D_{i1} is switched on for the 571 Wave 1 drivers who accepted fee free driving in the first week of the experiment and for the 255 drivers who bought a Taxi lease during the first week of the Taxi trial. 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 driving in Wave 1 and for the 619 drivers offered a Taxi lease during the first week of the Taxi trial.

For a set of weekly labor supply outcomes denoted by Y_{it}, the 2SLS setup for estimation of participation effects can be written:

$$Y_{it} = \alpha D_{it} + \beta X_{it} + \eta_{it} \tag{15}$$

$$D_{it} = \gamma Z_{it} + \lambda X_{it} + \upsilon_{it}, \tag{16}$$

where X_{it} includes dummies indicating the strata used for random assignment, driver gender, the number of months a driver has been on the Uber platform, one lag of log earnings, and indicators for whether a driver uses Uber's "vehicle solutions" leasing program and whether a driver has a car from model year 2003 or older.

As can be seen in Figure 7, both free week and Taxi offers 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 A6 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 A6 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 .41 and .30 in the high and low hours groups in response to Taxi participation and .35 and .36 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 reasonably constant Uber earnings opportunities, as hypothesized in our model of Uber and non-Uber work opportunities. Appendix Table A7 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 on surge, and the average rating on rated trips during the week. Consistent with the hours and earnings estimates, these results show clear increases in completed trips and the number of days with any driving in response to experimental incentives. Effects on other outcomes, however, including average hourly farebox and ratings, are small and not significantly different from zero.

Effects on the Distribution of Hours

Fee free driving and Taxi participation shifted the entire distribution of hours that treated drivers spent driving. This is clear from Figure 7, 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 $P[h_{1it} < \nu | D_{it} = 1]$.[10]

Figure 7 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 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.

4.2 Estimating the Uber ISE

The ISE for Uber hours is estimated by modifying (15) and (16), replacing the dependent variable, Y_{it}, with $\ln h_{it}$, and replacing the endogenous regressor, D_{it}, with $\ln w_{it}$. The hours variable, h_{it}, measures weekly hours with the Uber app toggled on; the log wage is average

[10] 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.

hourly earnings (that is, average hourly farebox net of the driver- and time-specific Uber fee). The 2SLS estimate of the coefficient on $\ln w_{it}$ is an estimate of the ISE, denoted δ^f in Section 2 (this is $\tilde{\delta}$ in the model with alternative jobs). Life-cycle logic suggests wealth effects from leasing should be small, so offers of Taxi leasing and fee-free driving should generate similar labor supply elasticities when estimated in the same population.

The first stage effect of Earnings Accelerator offers on log wages (γ in equation 16) depends on: (1) the experimental participation rate, and (2) the magnitude of experimentally-induced fee changes. To see this, let w_{it}^0 denote a driver's potential average hourly farebox in the absence of treatment. Participation decisions determine average hourly earnings through

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

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

$$\begin{aligned} &E[w_{it}|Z_{it}=1,t_0,t_1] - E[w_{it}|Z_{it}=0,t_0,t_1] \\ &\qquad = (t_0-t_1)E[w_{it}^0|D_{it}=1] \times P[D_{it}=1|Z_{it}=1]. \end{aligned} \tag{17}$$

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.[11]

The experimentally-induced proportional change in wages is obtained by dividing (17) by average hourly earnings for controls, $E[w_{it}|Z_{it}=0] = E[w_{it}^0](1-t_0)$. Assuming wages are similar for participants and other drivers, a claim supported by Table 3, the proportional wage increase generated by the Earnings Accelerator is:

$$\begin{aligned} &\frac{E[w_{it}|Z_{it}=1,t_0,t_1] - E[w_{it}|Z_{it}=0,t_0,t_1]}{E[w_{it}|Z_{it}=0,t_0,t_1]} \\ &\qquad = \frac{(t_0-t_1)}{1-t_0}P[D_{it}=1|Z_{it}=1]. \end{aligned} \tag{18}$$

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

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

25% fee is roughly $\frac{.25}{.75}.66 = .22$.[12]

The first stage characterized by equation (18) is generated by 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 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 almost 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).[13] The over-identified estimate of the (pooled-sample) ISE using Taxi variation falls to about 1.4. It's perhaps unsurprising that drivers who find Taxi leasing attractive are more elastic, but the gaps between the estimates using Taxi variation and those using opt-in week are modest.[14] In all cases, however, both 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 differences between low and high hours drivers. It's also noteworthy that the corresponding OLS estimates of equation (15), 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 the 23 percent of drivers who have zero hours in a given week.[15] But 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

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

[13]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.

[14]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.

[15]Over the four weeks of the experiment, an average of 74% of drivers chose to drive. When adding lagged earnings and hours controls we dummy out those who did not drive in the lagged week so as not to lose additional drivers.

conditioning seems innocuous.

Second, as discussed in Section 2.3, 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 it may be inappropriate to interpret our estimates of the ISE as conceptually similar to those estimated using survey data on total hours worked (see, for example, Card 1996). The most elastic alternative job response is likely to be reduced hours driving for Lyft. The appendix uses data on drivers with older vehicles to gauge the extent of cross-platform substitution. The results of this investigation suggest that drivers who cannot drive for Lyft or do not have access to Lyft's most generous promotions increased their Uber hours about as elastically as did other drivers. Although not entirely conclusive, this weighs in favor of a more general interpretation of the ISE estimates in Table 5.

5 Lease Aversion

Traditional cab drivers lease a medallion in advance of driving, possibly losing money if fares are scarce or non-work consideration such as driver health or the health of family members increase the opportunity cost of time spent driving. The Earnings Accelerator exposes drivers to the same sort of risk. In this section, we interpret driver response to this risk by integrating a model of "lease aversion," that is, the failure to exploit leasing gambles with positive expected value. An economic parameterization of lease aversion is integrated with statistical hypotheses about how drivers forecast their earnings when considering a lease.[16]

5.1 Modeling Taxi Take-up

Figure 9 plots observed Taxi opt-in rates against predicted participation rates for each of our sixteen Taxi contracts (four hours strata and commission groups times two treatments per group, in each of two weeks). The predicted take-up rates in this figure are calculated using the theoretical opt-in rule given by (14), with the pre-experiment opt-in week farebox

[16] See Chen et al. (2017) for an alternative analysis of dynamic driver behavior.

playing the role of wh_0. A value of $\delta^f = 1.2$ is used to compute the driver surplus produced by higher Taxi wages.[17]

The regression of observed participation rates on predicted participation rates plotted in Figure 9 shows that empirical Taxi opt-in rates average well below predicted. Why did so many drivers pass up a profitable opportunity to reduce their fees in return for a modest payment? Risk aversion seems like a natural explanation since fee elimination increases the proportional variance of earnings by $\frac{1}{(1-t_0)^2}$. But the degree of risk aversion required to explain lease aversion is arguably outside a plausible range. This conclusion is supported in the appendix, which uses data on expected gains and week-to-week farebox variation to calibrate the 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 extremely risk averse for concave utility alone to explain the degree of Taxi undersubscription observed here.

An alternative and perhaps more compelling explanation of low Taxi take-up is loss aversion. The decision to buy a lease may be a gamble that drivers hate to lose. Loss aversion isn't necessary to explain lease aversion; Chetty and Szeidl (2016) show that consumption commitments can also make moderate stakes gambles unattractive. But a simple model of loss aversion outlined in the theoretical appendix yields a one-parameter modification of the rule given by (14) that fits our data well.

In the spirit of Fehr and Goette (2007), our loss aversion model motivates a parameterization in which loss averse drivers treat a nominal lease cost of L as if this is κL for $\kappa > 1$. As in Andersen et al. (2014), this specification of loss aversion postulates a time-varying reference point. In this case, it seems natural to assume that the potential earnings realized under an Uber contract determines the reference point for Taxi. This produces a kink in the utility of earnings when farebox crosses the Taxi breakeven.

[17] The figure uses fareboxes of control drivers in the same hours stratum and commission as treated drivers. The predicted opt-in 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 and $\delta^f = 1.2$ 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.

Our 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, forecast y_{0i} is assumed to be distributed according to:

$$\ln y_{0i}|X_i \sim N(X_i'\beta_0, \tau_0^2), \tag{19}$$

where X_i includes opt-in week and/or earlier earnings and our experimental stratification variables. Using this and (11), the probability driver i opts-in 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 opt-in threshold reduction due to higher Taxi wages, and (L_i, t_i) describes the Taxi contract offered to this driver. Again, $\sigma(t_i)$ is computed using $\delta^f = 1.2$.[18]

Assuming forecasts are correct on average, β is identified from a regression of log farebox 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 opt-in decisions on $\hat{w}_i$ and a constant identify forecast variance and lease aversion parameters as transformations of the slope and intercept in this conditional probability function:

$$P[D_i = 1|L_i, t_i, X_i] = \Phi\left(\frac{1}{\tau_0}\hat{w}_i - \frac{1}{\tau_0}\ln\kappa\right). \tag{20}$$

The estimates of (20) reported in column 1 of Table 6 are from a model in which drivers make leasing decisions using a mean-preserving spread of the conditional farebox distribution observed during opt-in week. In other words, this model hypothesizes that the forecast distribution equals the observed opt-in week distribution with an additional variance component that causes forecast variance to exceed empirical variance. This model can be motivated by the fact that many drivers will not have known their completed opt-in week farebox at

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

the time they decided to lease (most opt-in decisions were made shortly after receiving the initial communication presenting the Taxi offer). This first specification is 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. The resulting estimate of κ is about 1.5, with an estimated forecast standard deviation roughly 115% larger than the root mean-squared error (RMSE) of the forecasting regression, (19).

The remaining columns of Table 6 show estimates from models using a forecasting equation that predicts farebox during the week Taxi drivers were exploiting their lease. These specifications were implemented using a version of X_i that includes farebox data from the Taxi opt-in week. Columns 3 and and 4 report the results of adding one and then two further farebox lags to the list of predictors.[19] The resulting estimates of κ, reported in columns 2-4 (along with bootstrapped standard errors computed as described in the empirical appendix), are remarkably stable, yielding lease aversion values around 1.5 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 beyond the conditional cross-sectional variance of earnings. At the same time, allowing for this extra uncertainty is insufficient to rationalize Taxi undersubscription. The estimates in columns 1-4 of Table 6 consistently indicate a degree of lease aversion captured by κ values around 1.5.

Nonparametric Lease Aversion

Control drivers' earnings are sampled from y_{0i}, so the extent of driver lease aversion is identified without assuming a parametric distribution for y_{0i}. To see this, note that incorporating lease aversion in the opt-in rule given by (11), drivers opt in to Taxi if

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

[19] All forecasting models include indicators for each of the eight hours × fee × 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 Taxi 1 includes data from the week in which Wave 2 was driving fee free. The 3rd lagged farebox for Taxi 1 includes data from the week in which Wave 1 was driving fee free. See appendix Figure A1 for timing details.

for any distribution of $\ln y_{0i}$. Writing p_{Lt} for the Taxi take-up 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:

$$\underbrace{F_0^{-1}(1 - p_{Lt})}_{\text{opt}-\text{out quantile}} = \ln \kappa + \ln \frac{L}{t} - \sigma(t) \tag{21}$$

The dependent variable here is the opt-out quantile for 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 10 plots the sample analog of $F_0^{-1}(1 - p_{Lt})$ against $\ln \frac{L}{t} - \sigma(t)$ for our 16 Taxi treatment combinations. With no 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, opt-out quantiles systematically exceed the adjusted log breakeven. The average gap between predicted and treated opt-out quantiles is summarized by the blue regression line, which has slope equal to that generated by a weighted regression of opt-out 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 set of opt-in quantiles is clearly shifted up, implying that drivers typically set a higher bar than the 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 value is reported in column 5 of Table 6, along with a bootstrapped standard error computed as described in the appendix. This estimate is similar to those from the parametric opt-in model, though considerably less precise. Interestingly, however, use of control drivers' farebox distribution during the week treated drivers were exploiting their lease generates a much larger estimate of κ, close to 7 (reported in column 6 of the table). This seems implausibly large, while the fact that the slope in this case is significantly below one suggests misspecification in the model using "live week" farebox as the relevant reference distribution. Moreover, the estimated κ in this specification is even less precise than the estimate in column 5. We therefore use the parametric estimates reported in columns 1-5 of the table (rounded to 1.5) for the CV calculations discussed below.[20]

The theoretical appendix shows that $\kappa = 1.5$ is consistent with a coefficient of loss aversion of about 2.5, not far from estimates reported in Tversky and Kahneman (1991). It's also noteworthy that data from the second-round Taxi subsample that had been offered Taxi in the first week generate values of κ similar to those estimated in the full Taxi sample. These results are reported in appendix Table A9 in a format similar to Table 6. Here too, parametric estimates of κ run around 1.5 (nonparametric estimates are exceedingly noisy in this subsample). This weighs against the hypothesis that our Taxi treatment was undersubscribed simply because drivers found it unfamiliar. On the other hand, estimates of the forecast variance in this subsample (τ) are mostly closer to the corresponding prediction equation RMSE than the corresponding estimates in the full sample. This suggests drivers exposed to Taxi twice responded with less uncertainty regarding the consequences.

6 Compensating Taxi

We computed average weekly CV for the sample of 19,316 active Boston drivers described in column 1 of Table 1. This sample drives more on average and therefore has higher weekly earnings than the sample of eligible drivers, which was drawn conditional on having average weekly hours between 5 and 25. Conditional on driving, the average weekly farebox in the Boston active sample is around \$541 in July 2016; weekly earnings are about \$423. This exceeds the average farebox (and earnings this implies) in Table 1 because here we're averaging over weeks rather than drivers and omitting weeks with zero earnings. Dropping zeros sidesteps the issue of how or whether to compensate inactive drivers who buy a lease: we might assume that inactive drivers neither drive Uber 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 6, an estimated $\delta^f = 1.2$, and an estimate of $\kappa = 1.5$.

Table 7 shows average weekly CV computed for a range of possible Uber-Taxi wage gaps

[20] It seems reassuring that the parametric estimates in column 1-4 align with the nonparametric estimates built around opt-in week data reported in column 5. Why not rely solely on a nonparametric model? The Normal model provides a parsimonious specification for covariates, while also identifying the degree of driver-specific uncertainty unrelated to covariates, the parameter τ_0. As an empirical matter, the residuals from a regression of log control farebox on the covariates used here fit a Normal distribution reasonably well.

and leases. Wage gaps are generated by the Uber fee, or by wage differences between Uber in an imagined world with only Taxi and restricted entry. As can be seen in Panel A of Table 7, 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 Uber 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 (the third entry in each cell indicates the proportion of drivers who prefer an Uber contract to leasing). About ten percent of drivers who opted in to our taxi treatments 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. Including these drivers increases average CV to $453.[21]

With lower lease costs, CV is naturally smaller; in some low-lease scenarios, Taxi is 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 Uber (median CV is $35; medians are reported in the second row of each cell). With a lease price of only $100, most drivers (54%) prefer Taxi. A natural summary measure of CV is the after-compensation lease price that sets CV equal to 0, that is, the lease rate that leaves drivers indifferent between Uber and Taxi. As can be seen in column 8, this averages $90 with a 15% wage gap and $434 with a 50% wage gap. These (average) 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 (6), this quantity is $t_0 w h_0 (1 + \frac{\delta t_0}{2(1-t_0)})$.

Lease averse behavior typically makes CV positive even for a lease cost of only $150: the Uber contract in this case generates average surplus of $62 with a 25% fee differential, though 50% higher Taxi wages make Taxi attractive to most drivers (40% still prefer Uber in this case). A lease of $108 equates Uber and Taxi with a 25% fee differential. Even with a lease as low as $100, however, most lease averse drivers prefer Uber to Taxi. These figures and other CV scenarios with lease aversion are summarized in Panel B of Table 7.

As can be seen in column 5 of Panel B of Table 7, with a $400 lease and a 25% wage

[21]CV including ten percent of drivers with zero hours driven under under a $600 lease is $.9 \times \$437 + .1 \times \$600 = \$453$.

difference, CV averages \$437, more than the nominal lease. Any excess of CV over the nominal lease can be interpreted as an interest payment to drivers in return for lending the 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 \$37 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.[22]

The comparisons in Table 7 implicitly make driving Taxi a condition for receipt of compensation. An alternative compensation scenario allows former Uber drivers to stop driving completely when the opportunity to drive Uber disappears, receiving UI instead (this is fanciful since Uber drivers who stop driving don't currently qualify for UI). As noted in Section 2, UI reduces the monetary cost of compensation by allowing former Uber drivers to be compensating in part through additional leisure. Section 2 derives a rule determining who sits out and the required UI replacement rate. The dollar compensation required to make idle Uber drivers as well off as they were when driving for Uber is reported in appendix Table A10, along with the proportion expected to take this option as determined by equation (4). The estimates in this table are computed allowing drivers to first choose Taxi or UI when Uber disappears, with those choosing UI awarded the UI replacement rate needed to return them to their starting point (given by equation (9)). Drivers who take up the opportunity to drive Taxi receive compensation according to equation (6).

Appendix Table A10 shows that the UI option greatly reduces the cash compensation required to make former Uber drivers indifferent to the disappearance of Uber. Importantly, however, the UI compensation option reduces consumer welfare. 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 reduces service by almost a third. Because appropriately 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

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

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 7 using the revenue from leasing, with some money left over. It's worth noting, however, that historically the revenue from medallion sales has not been redistributed to drivers.

The counterfactual implicit in this CV calculation is the temporary or anticipated disappearance of Uber, so that intertemporal substitution elasticities are the relevant characterization of driver labor supply. A long-term, unanticipated removal of Uber may have income effects, meaning the relevant elasticity for welfare comparisons is the (theoretically smaller) Hicksian substitution elasticity. A smaller elasticity makes Taxi less attractive, increasing the compensation required when Uber disappears. It's also interesting to imagine scenarios in which all ride-hailing platforms vanish. Labor supply is probably less elastic to the ride-hailing industry as a whole than to individual operators, so this scenario also tends to increase CV. At the same time, the distribution of total ride-share hours worked may differ from the distribution of Uber hours in our data. In this context, it's worth noting that 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

Driver surplus from ride-hailing is decreasing in the intertemporal substitution elasticity, which makes Taxi contracts more attractive since elastic drivers gain more from higher wages. On the other hand, surplus is increasing in a lease aversion parameter that raises nominal lease rates by the amount needed to induce Taxi participation under favorable lease arrangements. We interpret driver lease aversion as being generated by a coefficient of loss aversion around 2.5. Our randomized Taxi experiment identifies an ISE on the order of 1.2, but this is not large enough to overcome drivers' lease aversion. Consequently, the compensation required to make Uber drivers indifferent to the loss of Uber earnings opportunities is substantial and far exceeds the already mostly-positive CV computed using nominal lease rates.

Our economic analysis of ride-hailing focuses on the nature of the ride-hailing compensation contract. In principle, 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 compensation schemes based on a commission. The notion of an efficient bargain between workers and firms in an industry with rents has occupied labor economists since Mcdonald and Solow (1981). 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). Provided drivers are required to accept the Taxi contract as a condition for compensation, the required transfer can be funded by lease revenue. But this possibility rests on the assumption that drivers offered nominal CV in return for driving Taxi will take it.

It's also interesting to compare our results with the Mas and Pallais (forthcoming) 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 granting employers discretion when setting schedules. These findings seem consistent with the notion that it's the need to pay lease costs up front rather than hours constraints *per se* 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 ride-share upstart Fasten offered its drivers an $80 lease in return for "weekly unlimited driving," that is, driving with no fee. Fasten otherwise took a fee equal to a dollar a trip; this probably amounts to an average fee of around 10%. As can be seen in Panel B of Table 7, 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 $60. It's unsurprising, therefore, that Fasten no longer offers these contracts. Other evidence for lease aversion comes from developments at the New York City TLC, which recently began piloting "Fare Share contracts" allowing drivers to lease a medallion "for a set percentage of the farebox revenue".[23]

Looking down the road, a natural direction for further research on ride-hailing labor markets is an exploration of how the Taxi-Uber contractual contrast varies as a function of

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

market structure, such as the presence of competing ride-hailing services. More competition presumably means a more elastic labor supply response to individual platform operators, which should make Taxi contracts 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.

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	0.21***	0.19***	0.23***	0.12***	0.10***	0.13***
	(0.01)	(0.01)	(0.02)	(0.02)	(0.02)	(0.02)
2SLS	1.16***	1.22***	1.09***	1.83***	2.22***	1.45***
	(0.12)	(0.16)	(0.17)	(0.42)	(0.73)	(0.49)
Over-identified Model	1.19***	1.25***	1.13***	1.41***	1.57***	1.26***
	(0.12)	(0.16)	(0.17)	(0.27)	(0.40)	(0.37)
			B. OLS Estimates			
OLS	0.26***	0.27***	0.26***	0.14*	0.07	0.23*
	(0.06)	(0.08)	(0.08)	(0.08)	(0.09)	(0.13)
Drivers	1344	721	623	864	462	402
Observations	2485	1367	1118	1544	836	708

Note: This table reports 2SLS estimates of the intertemporal substitution elasticity (ISE). The endogenous variable is log wages, instrumented with dummies indicating treatment offers. 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 earnings and 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: Taxi Participation Models

	Parametric				Non-Parametric	
	(1)	(2)	(3)	(4)	(5)	(6)
Slope	0.66***	0.73***	0.81***	0.80***	0.98***	0.73***
	(0.09)	(0.09)	(0.08)	(0.08)	(0.09)	(0.09)
Intercept	-0.27***	-0.30***	-0.34***	-0.33***	0.45	1.91***
	(0.07)	(0.08)	(0.07)	(0.07)	(0.53)	(0.50)
Implied Kappa	1.51***	1.51***	1.52***	1.52***	1.57*	6.75*
	(0.12)	(0.11)	(0.10)	(0.10)	(0.93)	(3.93)
Implied Tau	1.52***	1.37***	1.24***	1.26***		
	(0.20)	(0.17)	(0.13)	(0.13)		
Forecasting regression RMSE	0.71	0.82	0.80	0.79		
Number of Drivers	954	938	938	938	954	938
Earnings Distribution	Predicted Opt-In Week	Predicted Live Week	Predicted Live Week	Predicted Live Week	Opt-In Week	Live Week
Number of Earnings Lags	1	1	2	3	N/A	N/A
Covariates	Yes	Yes	Yes	Yes	No	No

Notes: Parametric models are fit to micro data on participation using equation (20) in the text. Non-parametric models fit empirical quantiles using a version of equation (21)weighted by sample size. Standard errors are bootstrapped as described in the appendix. Each column uses data from the control drivers' earnings distribution.

Table 7: Compensating Variation

	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				
	-$15	$60	$135	$210	$510	$810	$1,110	$60
15%	$12	$87	$162	$237	$537	$837	$1,137	
	56%	80%	92%	97%	100%	100%	100%	
	-$50	$25	$100	$175	$475	$775	$1,075	$83
20%	-$13	$62	$137	$212	$512	$812	$1,112	
	45%	69%	83%	91%	100%	100%	100%	
	-$88	-$13	$62	$137	$437	$737	$1,037	$108
25%	-$40	$35	$110	$185	$485	$785	$1,085	
	37%	59%	74%	83%	98%	100%	100%	
	-$359	-$284	-$209	-$134	$166	$466	$766	$289
50%	-$231	-$156	-$81	-$6	$294	$594	$894	
	15%	29%	40%	49%	74%	87%	94%	

Notes: Panel A shows compensating variation (CV, paid to Uber 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 Uber. 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.

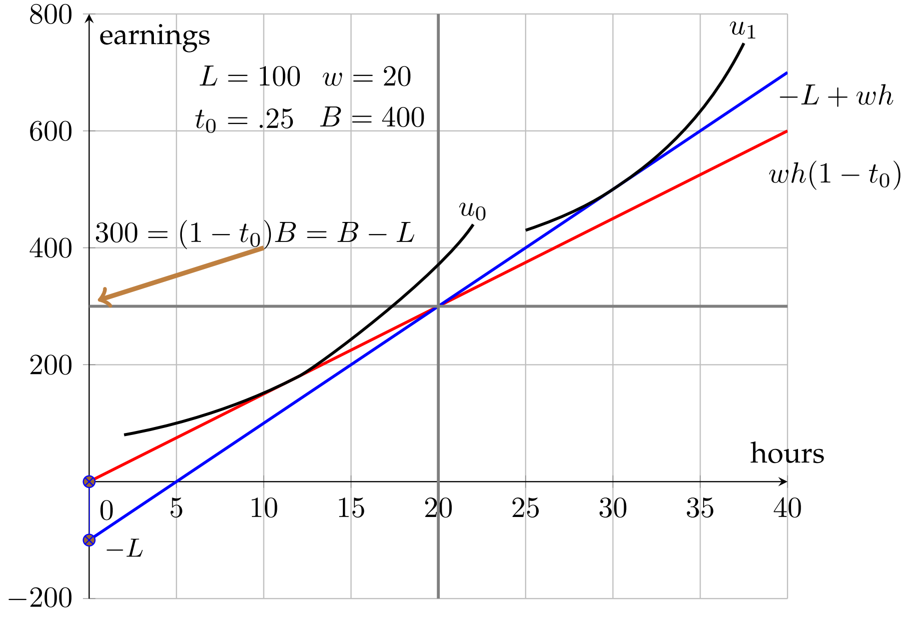


Figure 1: Uber and Taxi Budget Lines

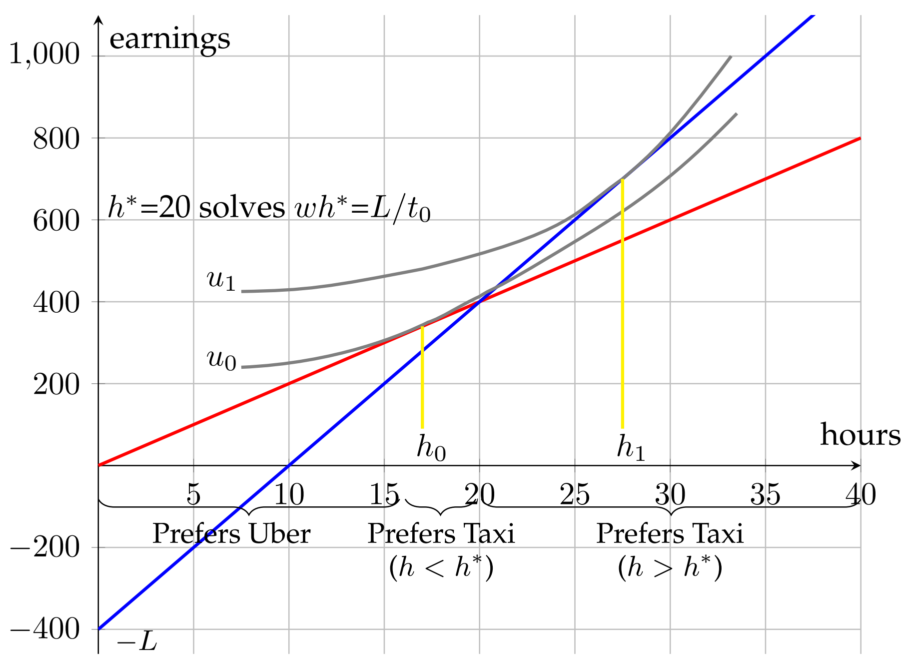


Figure 2: Driven and Elastic Drivers Opt for Taxi

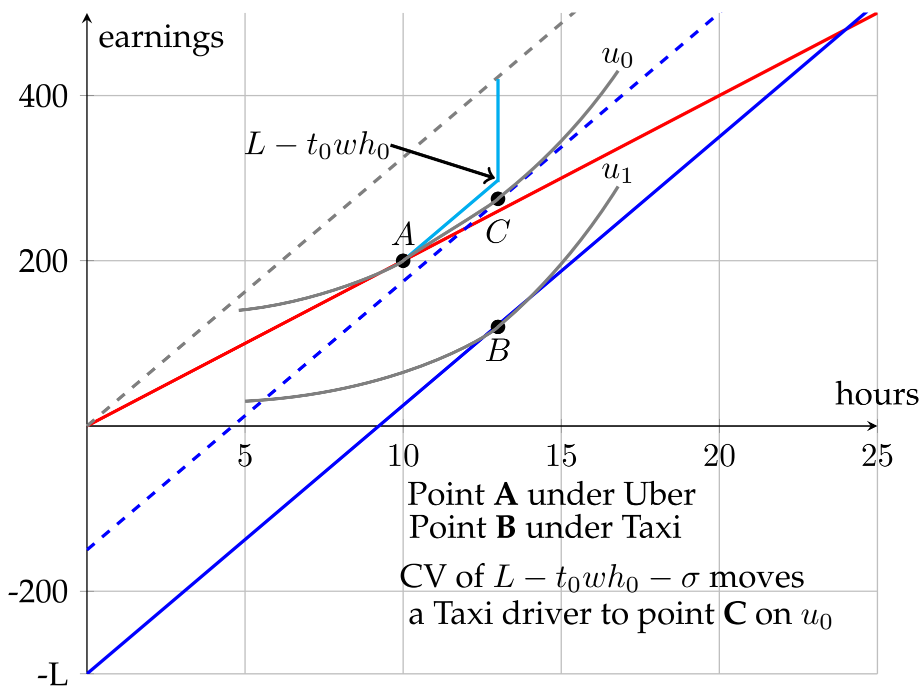


Figure 3: Uber vs Taxi Compensating Variation

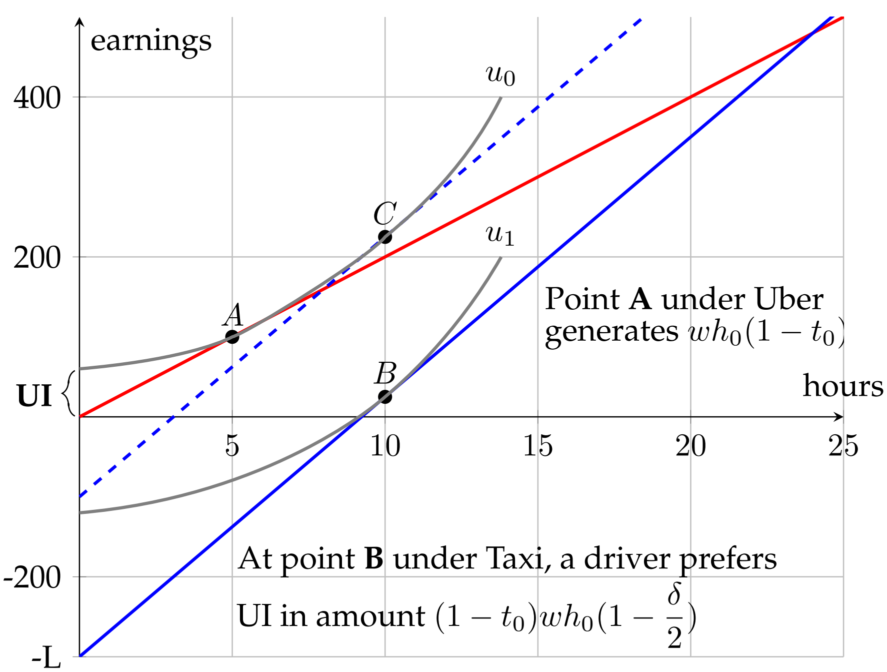
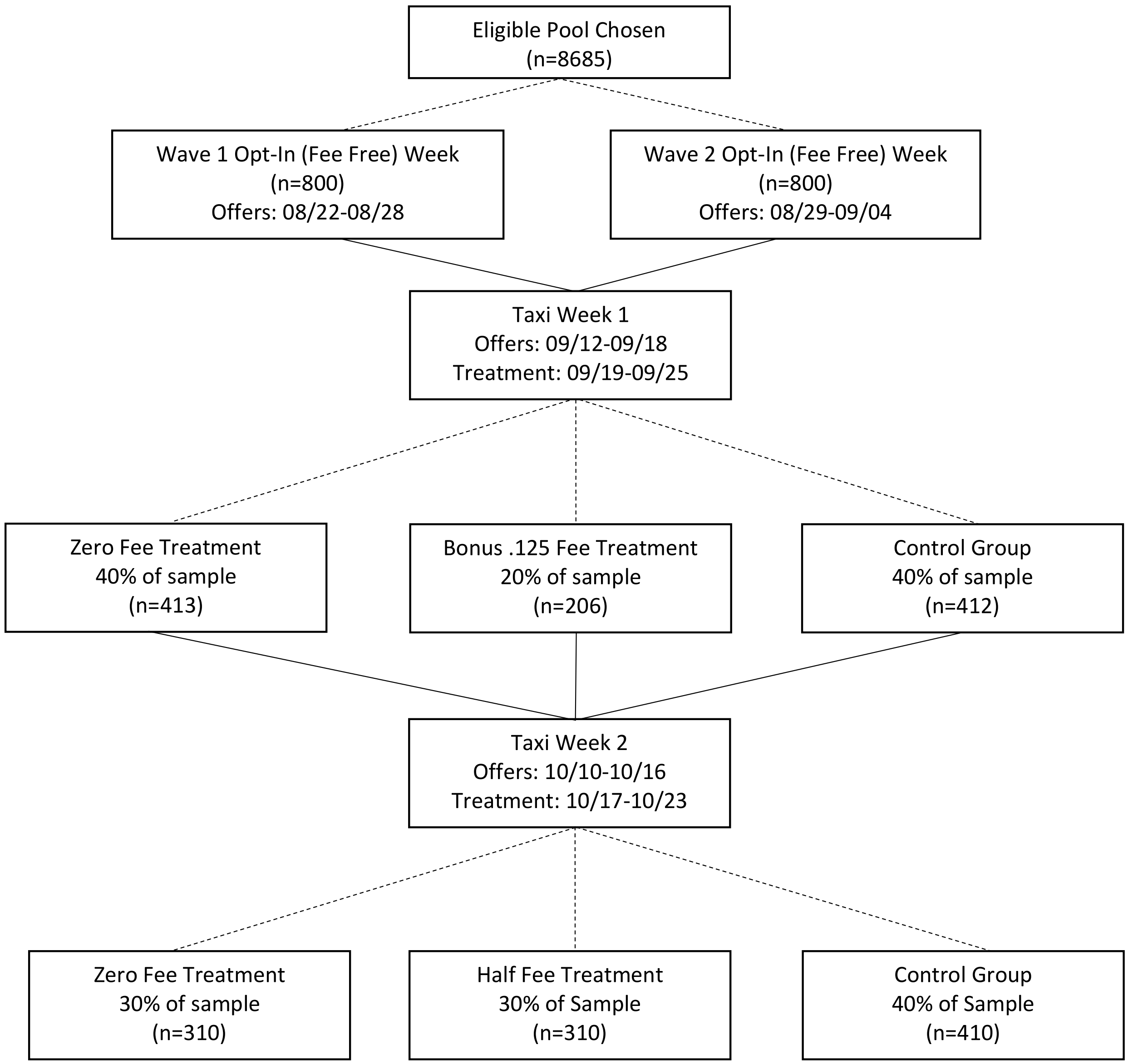


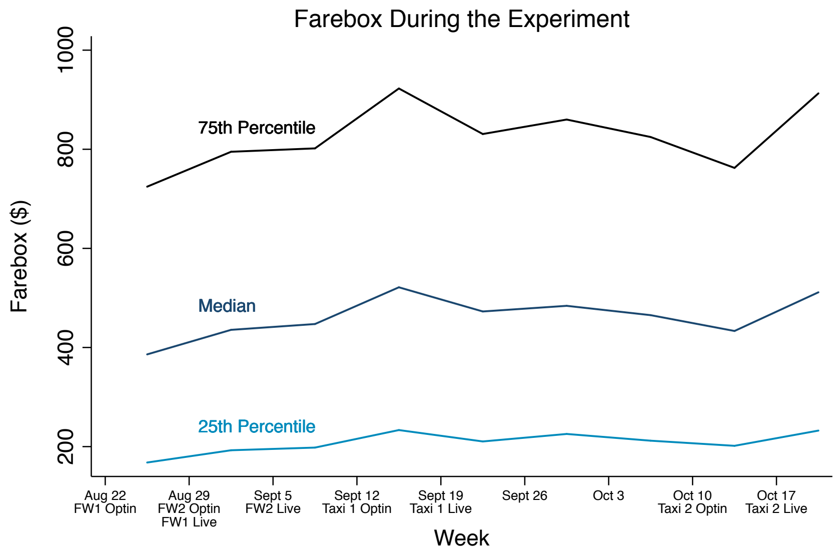
Figure 4: Uber vs Taxi Compensating Variation with UI

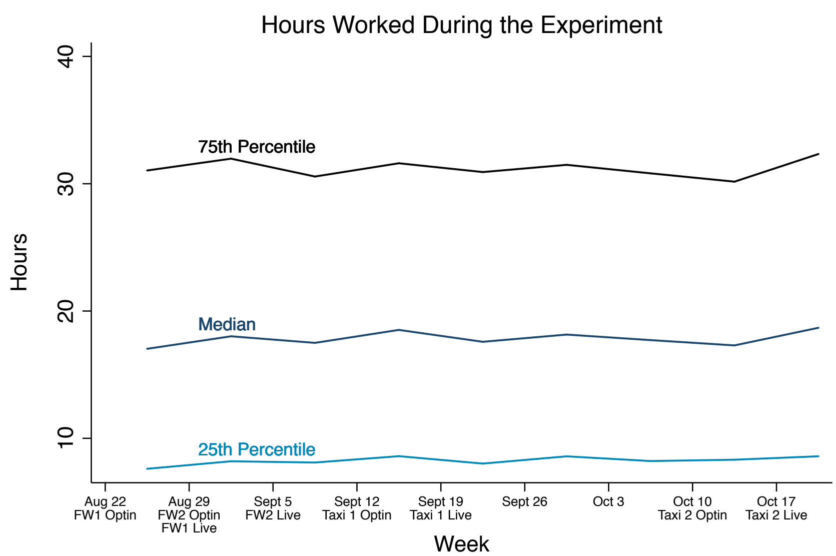
Figure 5: Earnings Accelerator Experimental Design



Note: dashed lines denote random assignment.

Figure 6: Boston Market Conditions

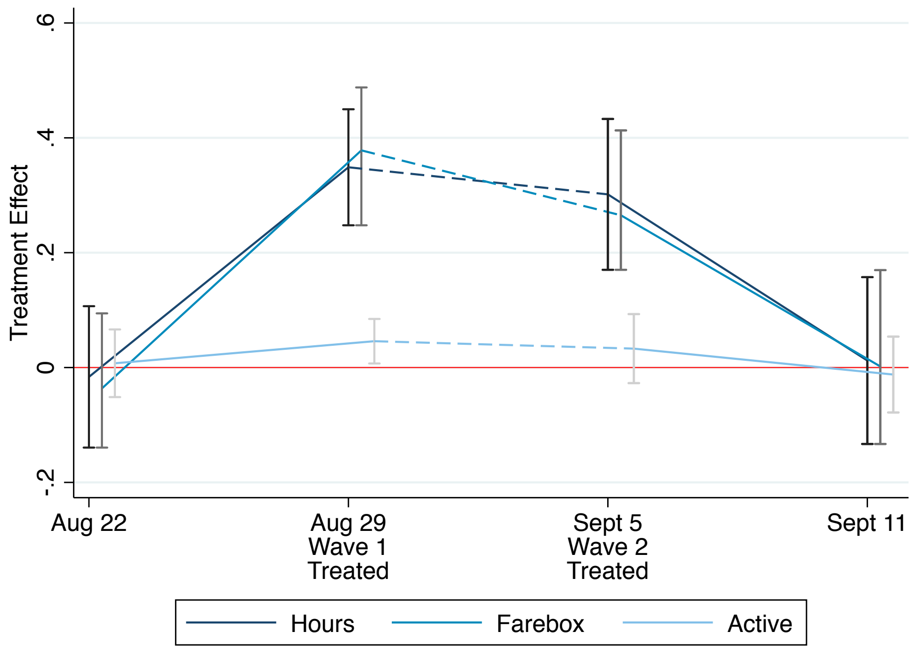




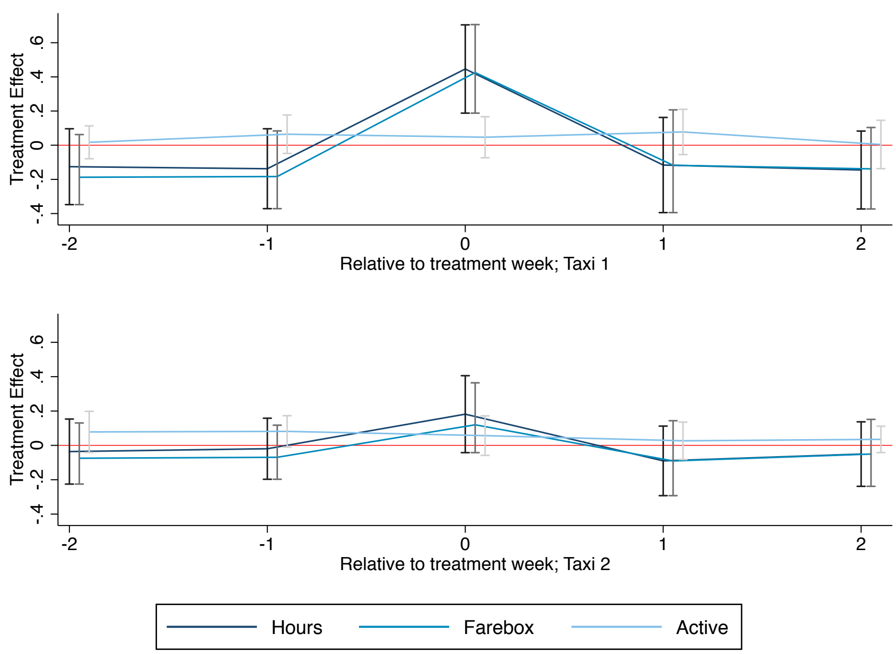
Notes: These figures show the evolution of farebox and hours worked (excluding promotions) over the course of the Earnings Accelerator experiment for the sample of eligible Boston drivers not selected for the experiment. Eligible drivers are those with valid vehicle year information who made at least 4 trips during the past 30 days and drove an average of between 5 and 25 hours/week in July 2016.

Figure 7: Participation Effects on Labor Supply

A. Opt-in Week

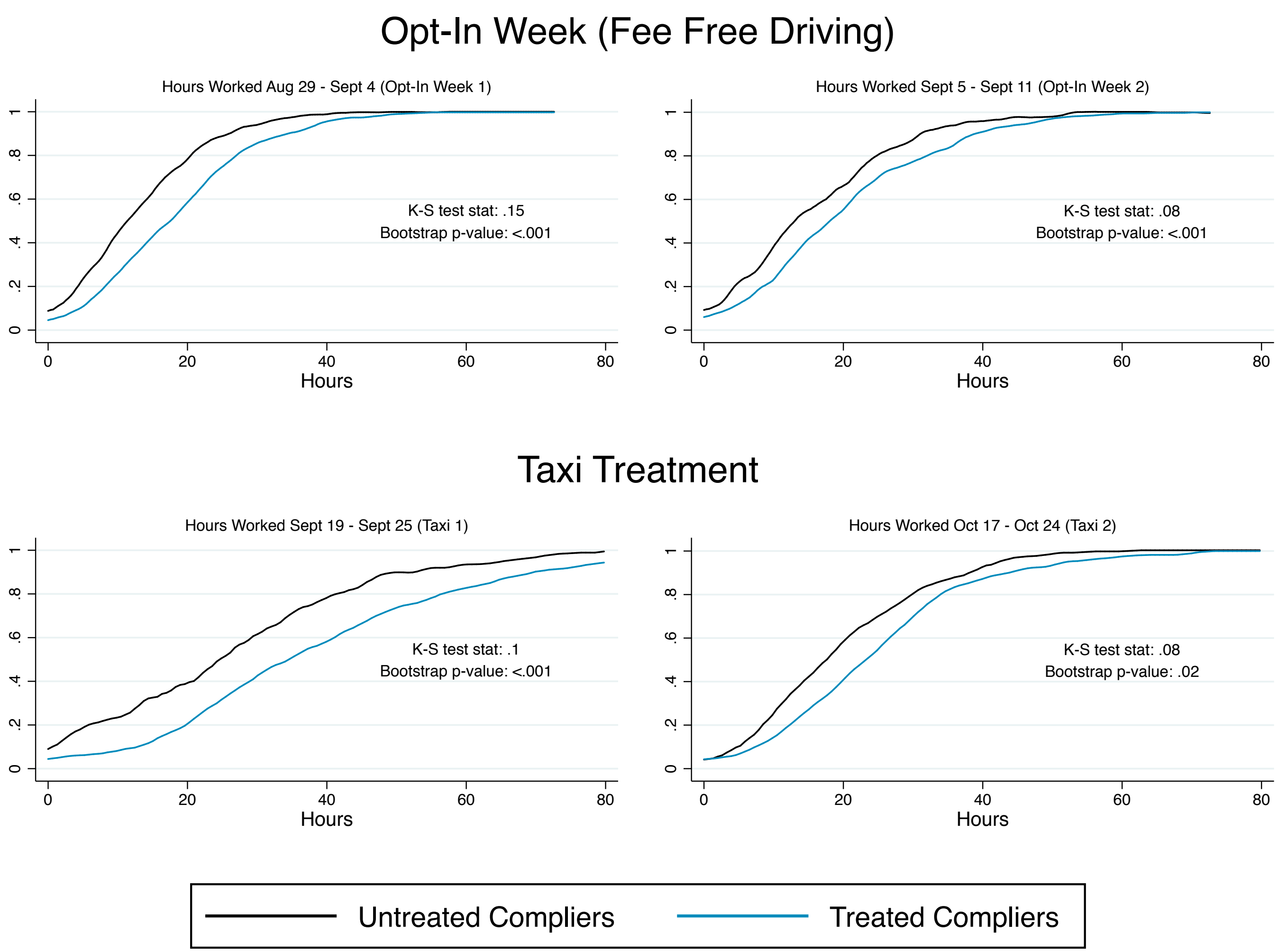


B. Taxi



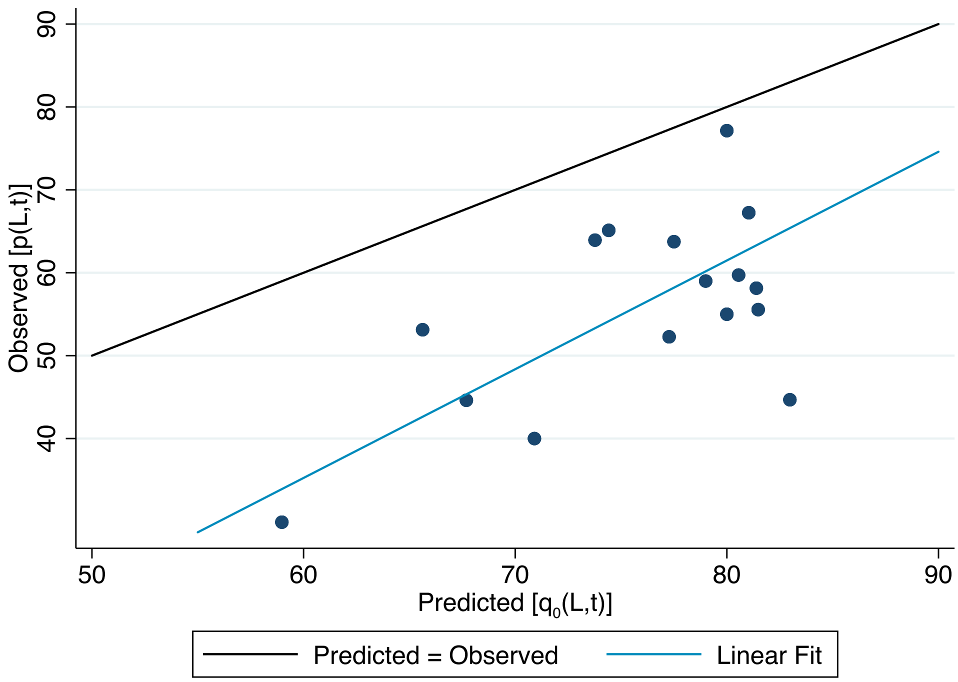
Note: These figures report treatment effects on hours, earnings and an indicator of any Uber activity for drivers who opted in to the Earnings Accelerator. Panel A reports estimates for drivers who accepted the opportunity to drive fee-free. Panel B reports estimates for drivers who bought a Taxi lease.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

Figure 8: Distribution Treatment Effects



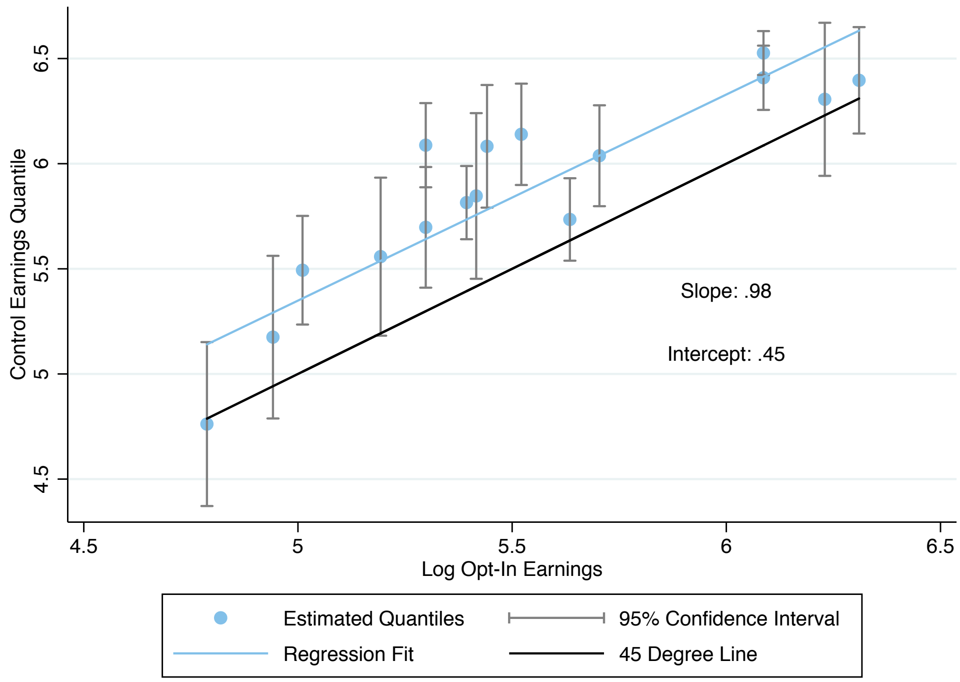
Notes: These figures report estimated CDFs of potential hours driven in treated and non-treated states for drivers who participated in the Earnings Accelerator. Top panels show estimates for drivers who accepted the opportunity to drive fee-free during the opt-in week. Bottom panels show estimates for 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.

Figure 9: 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 1.2. 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 10: Comparing Empirical and Theoretical Opt-in 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 opt-in 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

Who Takes UI?

Recall that the indifference curve attained under Taxi is labelled u_1. We identify the u_1 ordinate by assuming that drivers choose 0 hours when $w = L = 0$. Drivers for whom expenditure is negative at this point on u_1 prefer not to drive when faced with the Taxi compensation scheme. To determine who is in this category, we expand $s(0, u_1)$ around excess expenditure under Taxi, $s(w, u_1)$:

$$\begin{aligned} s(0, u_1) &= s(w, u_1) + (\frac{\partial s}{\partial w})(-w) + \frac{1}{2}\frac{\partial^2 s}{\partial w^2}w^2 \\ &= -L + (-h_1)(-w) + \frac{1}{2}(-\frac{\partial h^c}{\partial w}w^2). \end{aligned} \tag{22}$$

The second line here uses the fact that $s(w, u_1) + L = f(w, u_1; t = 0, L) = 0$. By definition, a lease-paying Taxi driver is on u_1, no transfer is needed to put him there.

Using

$$\frac{\partial h^c}{\partial w}w^2 = \frac{\partial h^c}{\partial w}\frac{w}{h_1}wh_1 = \delta wh_1,$$

the inequality $s(0, u_1) < 0$ can be written:

$$wh_1(1 - \frac{\delta}{2}) < L \tag{23}$$

This is equation (4) in the text.

Uber Theory with Alternative Jobs

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

- Uber: $f^a(w, \bar{u}; t_0, 0) = px^c - w(1 - t_0)h^c - e(a^c) = s^a(w(1 - t_0), \bar{u}) = s^a(w_0, \bar{u})$
- 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 an Uber driver as

$$s^a(w_0, u_0) = px_0 - w_0h_0 - e(a_0) - \lambda(u(x_0, l_0) - u_0),$$

where λ is the relevant Lagrange multiplier and subscript 0 indicates Uber demand and supply functions. 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 Uber parameters ensure that $\lambda u_l = w(1 - t_0) = w_0$ and $p = \lambda u_x$, so we can simplify:

$$\frac{\partial s^a}{\partial w} = \left(w(1 - t_0) - e'(a)\right)\frac{\partial a}{\partial w} - h_0 \tag{24}$$

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

$$\frac{\partial f^a}{\partial w} = -h_0, \tag{25}$$

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

As in the one-job world, Uber 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 (25):

$$f^a(w, u_0; 0, L) = s^a(w, u_0) + L \approx s^a(w_0, u_0) + L + \frac{\partial s^a}{\partial w}(tw) + \frac{1}{2}\frac{\partial^2 s^a}{\partial w^2}(tw)^2 \tag{26}$$

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

where derivatives are evaluated at Uber parameters, so Shephard's Lemma produces compensated Uber labor supply and its derivative. As before, Uber 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 Uber 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 Uber disappears is the difference in the excess expenditure functions evaluated at u_0, the utility obtained when the driver drives for Uber:

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

Rearranging (26) yields:

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

This is (6), with $\tilde{\delta}$ replacing δ.

What about UI with alternative jobs? The calculation that produces UI formula (9) goes through: the alternative job term disappears by virtue of Shephard's lemma. This reflects the fact that Shephard's lemma calculates the expenditure consequences of small changes. The disappearance of Uber, which can be modeled as a drop in the Uber wage to zero, may shift Uber hours into the alternative job. But the marginal earnings gained on the alternate job, $e'(a_0)$, equals the old Uber wage, $w(1-t_0)$. The change in alternate job hours in response to the changing Uber wage therefore has no net effect on excess expenditure, that is:

$$(w(1-t) - e'(a_0)) \frac{\partial a}{\partial w} = 0.$$

In practice, of course, some alternative jobs may not be very flexible, and the marginal gain from extra effort may fall below the Uber wage.

Finally, which alternative job holders choose to drive Taxi when Uber disappears? In a world with alternative jobs, excess expenditure under Taxi equals:

$$f^a(w, u_1; 0, L) = (px^c + L) - wh^c - e(a^c) = s^a(w, u_1) + L.$$

As before, we compute the opt-in rule by expanding $s^a(0, u_1)$ around $s^a(w, u_1)$.

$$s^a(0, u_1) = s^a(w, u_1) + (\frac{\partial s^a}{\partial w})(-w) + \frac{1}{2}\frac{\partial^2 s^a}{\partial w^2} w^2$$

Note that $s^a(w, u_1) = -L$ since here drivers are on u_1. In this case, however, the Taxi wage may be high enough to drive alternative job hours to zero, in which case $w > e'(a_1)$. The envelope theorem in this case leaves us with:

$$\frac{\partial s^a}{\partial w} = (w - e'(a_1))\,\frac{\partial a}{\partial w} - h_1 \tag{27}$$

But if alternative job hours are zero at Taxi wages, then the requirement that $a \geq 0$ implies $\frac{\partial a}{\partial w} = 0$ since higher Taxi wages must weakly reduce alternative job hours. The UI opt-in rule (22) therefore applies to the alternative job scenario.

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.[24]

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

$$E[u(w + x - L)] \approx u(w + E[x] - L) + \frac{1}{2}u''(E[w + x - L])\sigma_x^2 \tag{28}$$
$$E[u(w + [1-t]x] \approx u(w + (1-t)E[x]) + \frac{1}{2}u''(w + (1-t)E[x])(1-t)^2\sigma_x^2 \tag{29}$$

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, equa-

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

tions (28) and (29), we have:

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

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,

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

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 opted in (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.

	Bounds on Risk Aversion			
		Quantile		
	Mean	25th	50th	75th
Wealth	(1)	(2)	(3)	(4)
\$0	14.19	0.43	1.03	2.68
\$500	35.92	1.22	2.85	7.76
\$5,000	231.47	8.91	19.67	50.09
\$10,000	448.74	17.06	38.36	97.45
\$20,000	883.30	33.26	75.74	193.54
\$50,000	2186.97	82.28	187.74	481.79
\$100,000	4359.74	164.17	374.07	962.22

Loss Aversion Around an Uber Earnings Reference Point

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

$$u(x-r) = \begin{cases} \lambda(x-c) & x \geq c \\ \gamma\lambda(x-c) & x < c, \end{cases} \tag{30}$$

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 Uber 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 Uber 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 Uber earnings, Taxi driver utility in each state is

$$\begin{aligned} \text{high}: \ \lambda\left[W_H - L - W_H(1-t)\right] &= \lambda\left[tW_H - L\right] \\ \\ \text{low}: \ \gamma\lambda\left[W_L - L - W_L(1-t)\right] &= \gamma\lambda\left[tW_L - L\right]. \end{aligned}$$

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

$$p\lambda[tW_H - L] + (1-p)\gamma\lambda[tW_L - L] > 0, \tag{31}$$

since Uber 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 opt in when expected earnings exceed the Taxi breakeven. Writing W_L as a fraction π of L/t, the opt-in 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 $\kappa \approx 1.5$. 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

$$\gamma = \frac{1.5 - .53 - .27(1 - .53)}{(1 - .27)(1 - .53)} \approx 2.46$$

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 A8 presents estimates of the ISE from models of the form

$$\log h_{it} = \alpha \log w_{it} + \beta X_{it} + \eta_{it} \tag{32}$$

$$\log w_{it} = \gamma Z_{it} + \lambda X_{it} + \upsilon_{it} \tag{33}$$

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.

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 A11 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 A11 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 Parametric Opt-In Analysis

Bootstrap standard errors for the estimates reported in columns 1-4 of Tables 6 and Table A9 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 opt-in threshold reduction due to higher Taxi wages.

4. Estimate a Probit model for opt-in 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

Standard Errors for Non-Parametric Opt-In Analysis

Bootstrap standard errors for the estimates reported in columns 5-6 of Tables 6 and A9 were computed modifying steps 2-4 as follows:

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

2. Compute the fraction of treated individuals who opt-out of treatment in each of the 16 groups, that is, $1 - \hat{p}_{Lt}$

3. Compute the quantile of the log earnings distribution for the corresponding hours stratum, commission, and week, that is, $\hat{F}_0^{-1}(1 - \hat{p}_{Lt})$.

4. Regress the 16 quantiles $\hat{F}_0^{-1}(1 - \hat{p}_{Lt})$ from step 3 on estimated surplus-adjusted log breakeven, $\ln \frac{L}{t} - \hat{\sigma}(t)$, weighting by the number of treated drivers in each group

Figure A1: Taxi Messaging

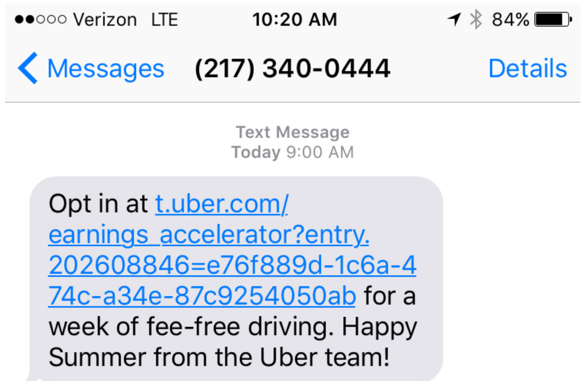


Figure A2: Taxi Slider

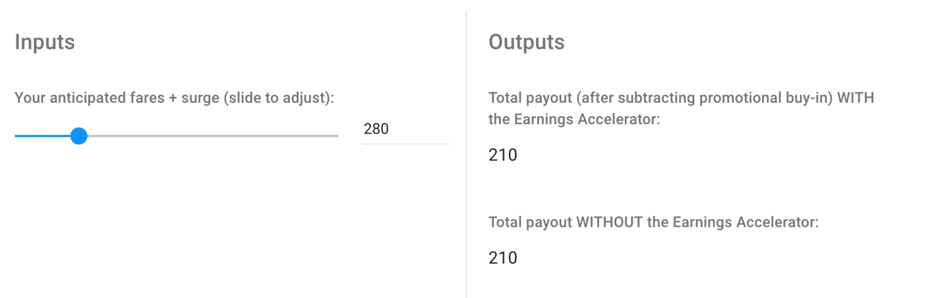


Table A1: Experimental Timeline

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

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 (1)	T=0 Treated Mean (2)	Half Fee Treated Mean (3)	T=0-Control Difference (4)	Half Fee-Control Difference (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 opted in to 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: Sample Sizes

	Opt-In Week		Taxi	
	(1)	(2)	(3)	(4)
	A. Pooled Sample			
Eligible	1600	1600	1031	1030
Positive Hours in Treatment Week	1302	1254	793	751
Positive Hours in Lagged Week	1181	1123	738	683
	B. High Hours			
Eligible	800	800	529	529
Positive Hours in Treatment Week	706	683	431	405
Positive Hours in Lagged Week	654	626	401	374
	C. Low Hours			
Eligible	800	800	502	502
Positive Hours in Treatment Week	596	571	362	346
Positive Hours in Lagged Week	527	497	337	309

Note: This table shows how the sample size changes with the use of log earnings and with the inclusion of lags of log earnings.

Table A6: Participation 2SLS Models for Labor Supply

	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	2.55	0.34***	2.80	0.34***	2.26	0.34***	2.69	0.32***	2.82	0.42***	2.54	0.22**
		(0.05)		(0.06)		(0.08)		(0.08)		(0.11)		(0.11)
		2556		1389		1167		1545		836		709
Log Earnings	5.84	0.36***	6.05	0.33***	5.59	0.38***	5.96	0.28***	6.08	0.37***	5.81	0.19
		(0.04)		(0.05)		(0.06)		(0.09)		(0.13)		(0.12)
		2486		1367		1119		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	-0.04	0.71	0.05
		(0.01)		(0.02)		(0.02)		(0.03)		(0.04)		(0.04)
		3200		1600		1600		2062		1058		1004
Log Hours	2.55	0.35***	2.80	0.35***	2.26	0.36***	2.69	0.37***	2.82	0.41***	2.54	0.30***
		(0.05)		(0.05)		(0.07)		(0.07)		(0.10)		(0.09)
		2556		1389		1167		1545		836		709
Log Earnings	5.84	0.37***	6.05	0.35***	5.59	0.40***	5.96	0.34***	6.08	0.37***	5.81	0.28***
		(0.04)		(0.05)		(0.06)		(0.08)		(0.11)		(0.10)
		2486		1367		1119		1545		836		709

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 A7: Participation 2SLS Models 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 A8: Estimates of the ISE 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 Model	1.16***	1.22***	1.10***	1.39***	1.73***	1.06**
	(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. 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 A9: Taxi Participation Models for Drivers Offered Taxi Twice

	Parametric				Non-Parametric	
	(1)	(2)	(3)	(4)	(5)	(6)
Slope	0.65***	0.93***	0.94***	0.90***	1.06***	0.92***
	(0.15)	(0.20)	(0.17)	(0.17)	(0.26)	(0.29)
Intercept	-0.07	-0.41**	-0.39**	-0.37**	-0.02	0.94
	(0.13)	(0.19)	(0.17)	(0.17)	(1.38)	(1.54)
Implied Kappa	1.11***	1.55***	1.52***	1.51***	0.98	2.55
	(0.20)	(0.21)	(0.19)	(0.20)	(2.97)	(19.35)
Implied Tau	0.67	1.07***	1.06***	1.11***		
	(0.35)	(0.23)	(0.20)	(0.21)		
Forecasting regression RMSE	0.67	0.83	0.80	0.78		
Number of Drivers	289	291	291	291	289	291
Earnings Distribution	Predicted Opt-In Week	Predicted Live Week (Controls)	Predicted Live Week (Controls)	Predicted Live Week (Controls)	Opt-In Week (Controls)	Live Week (Controls)
Number of Earnings Lags	1	1	2	3	N/A	N/A
Covariates	Yes	Yes	Yes	Yes	No	No

Notes: Parametric models are fit to micro data on participation using equation (20) in the text. Non-parametric models fit empirical quantiles using a version of equation (21)weighted by sample size. Standard errors are bootstrapped as described in the appendix. Each column uses data from the control drivers' earnings distribution. The sample used to construct the estimates in this table includes only drivers offered a Taxi contract twice.

Table A10: 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						
	-$23	$27	$65	$95	$159	$179	$183
15%	24%	43%	57%	67%	89%	97%	100%
	-5%	-14%	-25%	-36%	-73%	-92%	-98%
	-$57	-$6	$35	$67	$139	$165	$172
20%	23%	41%	54%	64%	87%	97%	99.3%
	-4%	-13%	-23%	-33%	-69%	-89%	-97%
	-$95	-$41	$2	$36	$117	$149	$159
25%	21%	39%	52%	62%	85%	95%	98.8%
	-3.8%	-11%	-21%	-31%	-65%	-86%	-96%
	-$362	-$301	-$247	-$200	-$65	$15	$62
50%	14%	27%	37%	46%	71%	84%	92%
	-1.8%	-6%	-11%	-16%	-41%	-62%	-78%

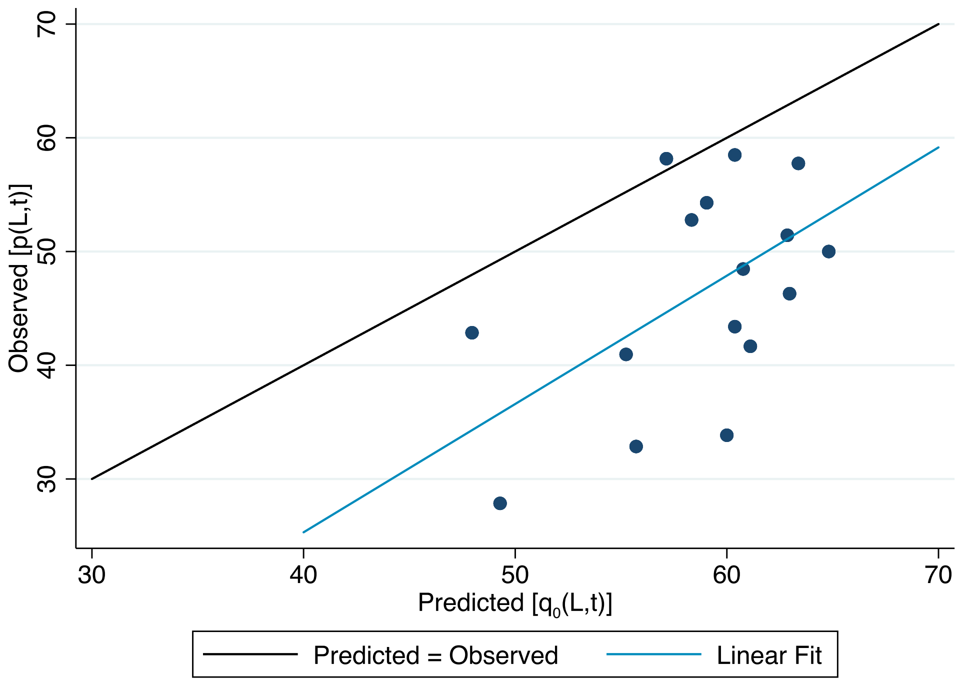
Notes: Panel A shows compensating variation (CV, paid to Uber drivers to induce them to work under Taxi), computed for the nominal lease rates listed in columns 1-7. Panel B evaluates CV using behavioral lease rates computed from Taxi take-up. The behavioral lease is fifty percent greater than the nominal 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 A11: 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	0.07		0.09*	0.17***	0.22***
	(0.05)	(0.03)	(0.05)	(0.02)	(0.03)
2SLS	1.16	1.27	1.18**	1.34***	1.32***
	(1.97)	(0.84)	(0.58)	(0.24)	(0.38)
OLS	0.22	0.14	0.09	0.16***	0.13
	(0.22)	(0.14)	(0.11)	(0.06)	(0.09)
Number of Observations	94	344	508	1653	1542
Number of Drivers	136	492	328	1181	841

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.

Figure A3: 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' earnings distribution during opt-in week. The red indicates the locus of equality for theoretical and empirical take-up. Rates use the full sample of drivers, including those who did not drive during opt-in week.