Monopsony Power in the Gig Economy

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Preliminary: comments are welcome.

Abstract

The self-employed increasingly provide services for customers via digital platforms. When these workers have unattractive outside options, platforms may exert monopsony power over them. In a two-sided ridesharing marketplace, platforms exploit this situation by raising their commission rate. However, unlike in wage-posting models, the final effect on wages depends on passenger pricing and the equilibrium response of worker utilization. Allowing a union of drivers to set the commission rate restores socially efficient pricing if the market for riders is competitive. Publicly available data on Uber's pricing and costs imply that this is the case; the platform faces strong competition for riders but has monopsony power over drivers. Consequently, commission rates are ten percentage points higher—and wages seven percent lower—than under the first-best commission rate.

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1 Introduction

Two-sided markets are notoriously complex but increasingly common given the recent proliferation of digital platforms. Broadly, these marketplaces are characterized by separate groups of agents interacting and affecting one another's outcomes through an intermediary (Rysman, 2009). The fact that behavioral responses on both sides of the market determine equilibrium outcomes makes it hard to infer the forces at play when researchers observe such marketplaces (Jullien et al., 2021).

Yet, the rise of gig work, where platforms mediate exchanges between buyers and sellers of labor services, has pushed the economics of two-sided markets into the spotlight (Garin et al., 2023). Our understanding of this new part of the labor market remains limited compared to settings where traditional models of wage posting and bargaining apply (Manning, 2011). For example, how does monopsony power manifest in the gig economy where platforms post prices and commission rates rather than wages?[1]

This paper develops a simple model to study a typical and important two-sided gig market: ridesharing. The model's parsimonious structure provides clear insights into the motivations behind platform pricing and the merits of alternative market designs. Further, I demonstrate the utility of the framework by using it to evaluate the extent of market power enjoyed by the US's largest rideshare platform, Uber, using only publicly available data.

The results suggest that Uber wields a substantial level of monopsony power over drivers but faces a competitive market for riders. Consequently, commission rates are ten percentage points higher than relative to a competitive benchmark. This causes the platform to charge lower prices than otherwise, which has the net effect of attenuating wage losses by raising driver utilization. Theoretically, allowing a union of drivers to set the commission rate restores this element of pricing to its first-best level because the passenger market is sufficiently competitive. This would cause wages to rise by seven percent.

Concretely, I consider a rideshare platform that operates a two-sided marketplace, and that sets the price of exchanges and receives a commission rate. Riders on the platform care about the price they face and the utilization of drivers, which maps to

[1] An agent has monopsony power when they can pay a lower unit price for a good or service if they buy a lower quantity. In the context of gig work, there is an ambiguity about whether platforms are buying labor that they then offer to customers, or whether customers are the buyers and platforms only mediate exchanges. I take the former view and, hence, treat platforms as potentially having monopsony power. However, in what follows, this is only an issue of semantics.

waiting times. Hourly wages, which also depend on utilization, determine the supply of drivers. The market reaches equilibrium through adjustments in worker utilization; the ratio of optimal rider demand and driver supply equals utilization in equilibrium. This exposition builds closely upon empirical and theoretical evidence in Hall et al. (2023), which describes and explains how rideshare markets equilibrate through worker utilization.

The model delivers several intuitions about decision-making by intermediaries. Platforms markup the commission rate when they enjoy monopsony power over drivers. Commission rates can be reformulated as keep rates for drivers which, equivalently, suffer a markdown. The form of this markdown is identical to textbook wage-posting models in monopsonistic labor markets that depend on the firm-level labor supply elasticity (Langella and Manning, 2021). To this extent, the platform-level driver supply elasticity is still a useful measure of monopsony power in this novel context. However, it is incomplete because the ultimate effect on wages and welfare also depends on demand elasticities.

If a platform faces perfect competition for drivers, then commission rates need not converge near zero for two reasons. Firstly, platforms must cover their costs. Secondly, a higher commission rate does not necessarily translate into higher wages since it affects the equilibrium utilization rate of drivers. In this case, the relative sensitivity of rider demand to waiting times and the price determines the commission rate. If rider demand is more sensitive to utilization than price, then commission rates are kept low to incentivize drivers to provide capacity. Conversely, if demand is more responsive to price, then the platform would rather stimulate demand with a lower price and keep a higher share of revenues.

The model also yields a traditional Lerner index for rider prices as a function of behavioral elasticities (Lerner, 1934).[2] In addition, when the platform faces a perfectly competitive market for drivers, the markup follows an augmented inverse elasticity rule. The ratio of profit to revenue from any transaction is optimally set equal to the inverse of the difference between the price elasticity and utilization elasticity of rider demand. This reflects the typical monopolist's trade-off between the behavioral and mechanical effects of a price change on profit with the additional concern that higher prices reduce waiting times through utilization, which offset the decline in demand.

Lastly, the model exhibits the "seesaw" principle (Rochet and Tirole, 2006). An in-

[2] Rochet and Tirole (2006) develop an alternative Lerner index in a two-sided market context, which is a function of opportunity costs.

crease in platform monopsony power unambiguously raises commission rates but, if passengers are sufficiently sensitive to waiting times relative to price, then this causes the platform to lower the price paid by riders. The overall effect on rider welfare is ambiguous because higher driver utilization can offset the beneficial effect of lower prices.

In summary, the model's structure explicitly and succinctly reflects a ridesharing market's two-sided nature. Three elasticities describe a platform's optimal choice of price and commission rate: (i) the elasticity of passenger demand to price, (ii) the elasticity of passenger demand to utilization, which determines wait times, and (iii) the elasticity of driver supply to hourly earnings. The small number of sufficient statistics makes it easy to estimate the model with little information, which is especially useful in a context where data is often proprietary. I illustrate this point with an application to the US's largest ridesharing platform, Uber.

Evaluating the extent of Uber's market power over the rideshare industry is an important issue in its own right. In the US alone, there are 1.5 million drivers earning money on the platform and over 6 million globally. Further, despite evidence that many workers benefit substantially from the opportunity to partake in ride-sharing markets and alike (Chen et al., 2019; Fisher, 2022), concerns remain about the welfare of individuals subject to these work arrangements (Prassl, 2018; Ravenelle, 2019). A plausible explanation for this anxiety is a fear that platforms benefit from monopsony power at the expense of drivers. This leverage may exist because platforms benefit from strong network effects and interact with a fissiparous workforce, as well as the fact that ridesharing entails a unique bundle of amenities that other jobs cannot offer.

Given this, establishing the existence (or lack) of monopsony power over workers in ridesharing markets, as well as potential antidotes, is a first-order policy question. Unfortunately, estimating monopsony power in this context is particularly difficult for at least three reasons. Firstly, gig platforms operate two-sided marketplaces so the usual approaches to estimating monopsony power do not apply. Secondly, microdata on the ridesharing industry is proprietary and researchers can only access this data at the behest of platforms.[3] To overcome these hurdles, I use the framework outlined above to reduce the data demands of estimation while fully engaging with the two-sided nature of these markets.

Thirdly, drivers' labor supply is hard to measure (Harris and Krueger, 2015). Inter-

[3] There are notable efforts to scrape data on ridesharing and related markets, see Rosaia (2020) and Sullivan (2022). The EU's new Data Act may also pave a route to avoid this issue.

mediaries typically record "online" hours, but this measure does not map to a concept of *genuine* labor supply because the online status is costless to maintain. For example, a worker may be multi-apping or have no real intention of accepting a job while appearing online for a platform. This difficulty has inhibited policy interventions, such as a minimum wage, in ridesharing markets. I circumvent this issue by inferring a genuine driver supply elasticity from platforms' pricing decisions. Note that this does not require platforms to observe a measure of genuine labor supply. Instead, they can optimize through experimentation.

Uber is well suited to the analysis set out in this paper. The firm sets the price of rides that drivers complete for passengers on its platform and receives a share of the fare. Although the exact commission rate varies from ride to ride, in the words of Uber's CEO, Dara Khosrowshahi, "[the platform] optimizes for an average take-rate".[4,5] Moreover, passengers care about prices and utilization because of wait times and, naturally, earnings determine drivers' labor supply. Thus, the platform's pricing in the marketplace and its participants satisfy the model's core assumptions.

To pin down the driver and rider elasticities that Uber faces I use publicly available information on a combination of the platform's commission rate, costs, and the equilibrium response of utilization to price changes. Public sources often discuss estimates of these numbers, which have also been reported in academic papers using proprietary data. Given the evidence available, this study focuses on Uber's US rideshare marketplace in the years leading up to 2017.

The model's definition of a commission rate is the fraction of the fare paid by riders that drivers do not receive. This differs from the 20 percent fee that Uber publicizes because some of the fare is earmarked to cover costs. Using proprietary data, Castillo (2020) reports an average commission rate of 26.3% for Houston, Texas, in early 2017. Anecdotal evidence from service fee summaries provided by Uber to drivers is also consistent with these numbers. Notably, Uber's commission rate had been increasing until 2017 (Caldwell and Oehlsen, 2021), and public financial filings indicate that the commission rate may have risen significantly since the pandemic.[6]

Uber's primary marginal costs for mediating exchanges are transaction fees for processing payments, sales tax payable, and insurance for drivers that covers "life-changing events". Again, Castillo (2020) reports that the first two costs constitute

[4] See Dara's interview with The Rideshare Guy here.

[5] The "take rate" is another phrase for the commission rate.

[6] The ratio of revenue to gross bookings in Uber's 10-K filings increased by around one-third in 2022, from approximately 20 percent to 27 percent.

three percent of the fare. Estimates of the average fare, average trip distance, and per-mile insurance costs imply that insurance premiums comprise just over 12 percent of any fare. Therefore, in total, 15 percent of the fare equals the cost to Uber of facilitating the exchange. To deal with uncertainty in this number, I study a range of costs.

The final ingredient is the elasticity of equilibrium utilization to price, which Hall et al. (2023) estimates using pricing experiments conducted by Uber between 2014 and 2017 in US cities. This study suggests that in response to a 10% increase in price, utilization falls by 14% in the long run. Since the decrease in utilization exceeds the increase in prices, this evidence suggests that fare rises reduce wages on net.

Informed by this data, the results suggest that Uber faces a very competitive market for riders but exerts substantial monopsony power over drivers. The central scenario implies that the platform faces a precisely estimated elasticity of driver supply to wages of 6.71. Viewed through the model, this implies a ten percentage point markup of the commission rate. However, unlike in wage-posting models, this does not directly translate into a wage markdown because ridesharing markets equilibrate through utilization, which affect hourly earnings.

It is necessary to consider a precise counterfactual to understand the impact of monopsony power in rideshare markets on wages and, ultimately, worker welfare. The theoretical framework implies that setting the commission rate to maximize wages restores the first-best commission rate when the market for riders is sufficiently competitive. Since this is the case for Uber, I study setting the commission rate to the competitive labor market benchmark while leaving all else equal, noting that this could be achieved by allowing drivers to unionize.

In this scenario, a commission rate fall of ten percentage points triggers the platform to raise prices by approximately one-third. In turn, this causes utilization to fall by half so that, overall, wages rise by seven percent. Under an isoelastic labor supply assumption, these wage gains precipitate a large increase in worker welfare. The driver surplus is estimated to rise by over 50 percent. Therefore, this paper suggests that monopsony power poses a major hurdle to unlocking the full potential of the gig economy for workers.

This paper proceeds as follows: section 2 develops a model of a ridesharing market, section 4 combines this theory with data for Uber, and section 5 concludes.

2 Model of a Two-Sided Ridesharing Marketplace

This section develops a model of a two-sided ridesharing market that builds upon the framework of Hall et al. (2023) by explicitly considering the platform's price setting. I save most points of discussion for the end of the section to allow for a clear exposition.

2.1 Market Participants and Equilibrium

This subsection describes how I model the decisions of the different agents who interact in the marketplace, as well as the definition of equilibrium in the model.

Drivers. Rideshare drivers decide how much to work on the platform according to the wage rate that they can earn. This is summarised by a driver supply function $H(w)$, which depends on hourly wages w and determines the number of supply hours available to the platform. The function comprises both extensive and intensive margin labor supply responses to changes in earnings. In ridesharing markets, intensive margin labor supply responses extend beyond choosing how many hours to work conditional on working. For example, intensive margin responses may include how devoted workers are to the platform, which can take the form of geographical positioning and acceptance rates. In this sense, $H(w)$ reflects a quality-adjusted measure of driver hours.

Hourly wages depend on the price per hour of transportation p that the platform charges, the fraction of fares that drivers retain θ (*i.e.*, one minus the commission rate), and the proportion of supply hours that drivers are transporting passengers x (*i.e.*, the utilization rate). Taken together, hourly earnings are given by

$$w = p \cdot \theta \cdot x. \tag{1}$$

Riders. Passengers demand hours of transportation which is described in a reduced form via a demand function $D(p, x)$. Their demand depends on the price of this service and utilization, which I assume determines waiting times. This assumption has two alternative microfoundations. Firstly, under a constant returns-to-scale matching function between drivers and riders, waiting times are solely a function of the utilization rate and structural parameters of the matching technology (Cullen and Farronato, 2021). Hall et al. (2023) argues that this is a reasonable approximation in the context of Uber. Secondly, queuing theory finds that utilization plays a key role in determining waiting times, most famously in Kingman's equation (Kingman, 1961).

Equilibrium. The marketplace reaches equilibrium through adjustments in utilization rather than price because the latter is set by the platform. In particular, given a price and a commission rate, equilibrium requires that

$$D(p,x) = x \cdot H(p \cdot \theta \cdot x). \tag{2}$$

This implies that equilibrium utilization equals the ratio of optimally chosen demand and supply of ridesharing hours. Hall et al. (2023) document empirically how ridesharing markets equilibrate through utilization. A unique equilibrium exists if $\frac{\partial H(w)}{\partial w} > 0$, $H(w) \to 0$ as $w \to 0$, $H(w) \to \infty$ as $w \to \infty$, $\frac{\partial D(p,x)}{\partial x} < 0$, and $D(p,x) \geq 0$, which I assume for the remainder of the paper.

2.2 The Platform

A platform selects a price and commission rate to maximize profits but is constrained by the equilibrium adjustment of driver utilization, which also encapsulates driver and rider behavior. Formally, platforms face the following problem

$$\max_{p,\theta} \, \big[p \cdot (1-\theta-\tau) - c\big] \cdot D(p,x) \text{ subject to } D(p,x) = x \cdot H(p \cdot \theta \cdot x), \tag{3}$$

where τ represents costs that are proportional to the fare (*e.g.*, transaction fees) and c denotes other costs of mediation (*e.g.*, insurance premiums). Platform optimization yields two first-order conditions for p and θ, respectively,

$$1 + \mu^* \cdot \big(\varepsilon_{D,x} \cdot \varepsilon_{x,p} - \varepsilon_{D,p}\big) = 0, \tag{4}$$

$$-\frac{\theta^*}{1-\theta^*-\tau} + \mu^* \cdot \varepsilon_{D,x} \cdot \varepsilon_{x,\theta} = 0, \tag{5}$$

where $\varepsilon_{D,x} = -\frac{\partial D(\bullet)}{\partial x} \cdot \frac{x}{D(\bullet)}$, $\varepsilon_{D,p} = -\frac{\partial D(\bullet)}{\partial p} \cdot \frac{p}{D(\bullet)}$, $\varepsilon_{x,p} = -\frac{dx}{dp} \cdot \frac{p}{x}$, $\varepsilon_{x,\theta} = -\frac{dx}{d\theta} \cdot \frac{\theta}{x}$, and $\mu = \frac{p\cdot(1-\theta-\tau)-c}{p\cdot(1-\theta-\tau)}$. The latter term is a measure of markup known as the Lerner index (Lerner, 1934), which equals the share of platform revenue that is profited from one hour of ridesharing. Asterisks denote optimally chosen endogenous variables.

Equation (4) shows that raising prices mechanically increases revenue but simultaneously impacts demand via two behavioral channels. Firstly, higher prices reduce demand in the traditional sense. Secondly, higher prices raise wages, which encourages higher driver supply and, in turn, reduces utilization and increases demand. Equation (5) follows an analogous logic for the setting of commission rates. Raising the commission rate leads to more revenue but also increases utilization due to lower wages that discourage driver supply and, eventually, decrease demand.

Comparative statics on the equilibrium condition described by equation (2) provide two more equalities that connect the demand and supply elasticities

$$\varepsilon_{x,p} = \frac{\varepsilon_{D,p} + \varepsilon_{H,w}}{\varepsilon_{D,x} + 1 + \varepsilon_{H,w}}, \tag{6}$$

$$\varepsilon_{x,\theta} = \frac{\varepsilon_{H,w}}{\varepsilon_{D,x} + 1 + \varepsilon_{H,w}}, \tag{7}$$

where $\varepsilon_{H,w} = \frac{\partial H(\bullet)}{\partial w} \cdot \frac{w}{H(\bullet)}$. Equilibrium utilization responds more strongly to a change in price than to a change in the commission rate because the former affects both drivers and riders directly.

Theorem 1 (The platform's optimal pricing)**.** *The platform's optimal markup and commission rate can be expressed as a function of elasticities that describe driver and passenger behavior as follows*

$$\mu^* = \frac{1 + \varepsilon_{D,x} + \varepsilon_{H,w}}{\varepsilon_{D,p} + \varepsilon_{H,w} \cdot (\varepsilon_{D,p} - \varepsilon_{D,x})}, \tag{8}$$

$$1 - \theta^* = 1 - (1 - \tau) \cdot \frac{\varepsilon_{D,x}}{\varepsilon_{D,p}} \cdot \frac{\varepsilon_{H,w}}{1 + \varepsilon_{H,w}}. \tag{9}$$

Proof. Substituting equations (6) and (7) into the first-order conditions (4) and (5), and rearranging gives expressions (8) and (9). Second-order conditions and corner solutions are considered in the appendix. □

Below, I assume that the functions $D(\bullet)$ and $H(\bullet)$ are isoelastic in all their arguments. In other words, I treat $\varepsilon_{D,p}$, $\varepsilon_{D,x}$, and $\varepsilon_{H,w}$ as structural parameters that are invariant to counterfactual scenarios. Further, I assume that $\varepsilon_{D,p} > 1$.

The platform's pricing can differ from the social optimum because it may exert market power over either side of the market. Socially efficient pricing maximizes the sum of platform profits, and rider and driver surplus subject to participants' incentives, which are embedded in the equilibrium condition. Formally, the social planner faces the following problem

$$\max_{p,\theta} \; \big[p \cdot (1-\theta-\tau) - c\big] \cdot D(p,x) + \frac{p \cdot D(p,x)}{\varepsilon_{D,p}-1} + \frac{w \cdot H(w)}{1+\varepsilon_{H,w}}$$
$$\text{subject to } \; D(p,x) = x \cdot H(p \cdot \theta \cdot x). \tag{10}$$

The social planner places equal weight on the platform's profits, rider surplus, and consumer surplus, which take a convenient form because the demand and supply functions are isoelastic. The social planner's objective function can be rewritten as a parameterization of the platform's problem, after incorporating the equilibrium constraint, as follows

$$\left[p \cdot \left(\frac{\varepsilon_{D,p}}{\varepsilon_{D,p}-1} - \frac{\varepsilon_{H,w}}{1+\varepsilon_{H,w}} \cdot \theta - \tau\right) - c\right] \cdot D(p,x). \tag{11}$$

The optimality conditions take a similar form but explicitly account for the impact of pricing changes on market participants. The social planner's first-order conditions for p and θ, respectively, are

$$1 + \tilde{\phi} \cdot \big(\varepsilon_{D,x} \cdot \varepsilon_{x,p} - \varepsilon_{D,p}\big) + \frac{\tilde{\theta}}{\frac{\varepsilon_{D,p}}{\varepsilon_{D,p}-1} - \tilde{\theta} - \tau} \cdot (1 - \varepsilon_{x,p}) = 0, \tag{12}$$

$$\varepsilon_{x,\theta} \cdot \left(\tilde{\phi} \cdot \varepsilon_{D,x} - \frac{\tilde{\theta}}{\frac{\varepsilon_{D,p}}{\varepsilon_{D,p}-1} - \tilde{\theta} - \tau}\right) = 0, \tag{13}$$

where $\phi = \frac{p \cdot (\frac{\varepsilon_{D,p}}{\varepsilon_{D,p}-1} - \theta - \tau) - c}{p \cdot (\frac{\varepsilon_{D,p}}{\varepsilon_{D,p}-1} - \theta - \tau)}$ and the notation $\tilde{\bullet}$ reflects endogenous parameters evaluated at the social optimum. There are two key differences with the platform's first-order conditions. First, the object ϕ is similar to the Lerner index μ but incorporates the welfare of riders through the term $\frac{\varepsilon_{D,p}}{\varepsilon_{D,p}-1}$. Second, the conditions incorporate the effect of changes in pricing on wages, which summarizes the impact on driver welfare because of the envelope condition.

Theorem 2 (Socially efficient pricing)**.** *The socially efficient markup and commission rate can be expressed as a function of elasticities that describe driver and passenger behavior as follows*

$$\tilde{\phi} = \frac{1}{\varepsilon_{D,p} - \varepsilon_{D,x}}, \tag{14}$$

$$1 - \tilde{\theta} = 1 - \left(1 - \tau + \frac{1}{\varepsilon_{D,p}-1}\right) \cdot \frac{\varepsilon_{D,x}}{\varepsilon_{D,p}}. \tag{15}$$

Proof. This follows from solving equations (14) and (15) for $\tilde{\phi}$ and $\tilde{\theta}$. Second-order conditions and corner solutions are considered in the appendix. □

To learn more about these markup and commission rate formulae, I provide two brief definitions. Then I discuss the implications of the derivations above for optimal platform pricing relative to first-best pricing.

Definition 1 (Perfect competition for drivers)**.** *$\varepsilon_{H,w}$ converges to infinity.*

Definition 2 (Perfect competition for riders)**.** *Both $\varepsilon_{D,p}$ and $\varepsilon_{D,x}$ converge to infinity, and $\frac{\varepsilon_{D,x}}{\varepsilon_{D,p}}$ converges to $\kappa \in (0, \frac{1}{1-\tau})$. This implies that $\varepsilon_{D,p} - \varepsilon_{D,x}$ converges to infinity.*

There are two noteworthy points about socially efficient pricing. First, it does not depend on the labor supply of drivers. Second, socially efficient pricing coincides with the platform's pricing when there is perfect competition in both the rider and driver markets. For the commission rate this follows trivially because $\frac{1}{\varepsilon_{D,p}-1}$ and $\frac{\varepsilon_{H,w}}{1+\varepsilon_{H,w}}$ converge to zero and one, respectively, in this case. From this observation, it is apparent that ϕ converges to μ. It remains to show that μ^* converges to equation (14), which I explain below when discussing the platform's incentives.

The clearest implication of the platform's optimal commission rate (9) is that platforms use monopsony power to raise their commission rate. Relative to a scenario with perfect competition for drivers, the commission rate is $100 \times \frac{\varepsilon_{D,x}}{\varepsilon_{D,p}} \cdot \frac{1-\tau}{1+\varepsilon_{H,w}}$ percentage points higher. *Ceteris paribus*, this is equivalent to to suppressing workers wages by $\frac{1}{1+\varepsilon_{H,w}}$ percent, which mimics the mark down in one-sided models of monopsony power with wage-posting (Manning, 2011). However, in the two-sided market context, commission rate markups do not directly translate to wage markdowns because there are pricing responses on the other side of the market and equilibrium effects on utilization. I explore this mechanism later in the paper when considering counterfactual market designs.

Interestingly, commission rates need not converge to zero absent any monopsony power. In particular, the commission rate under perfect competition for drivers equals

$$\lim_{\varepsilon_{H,w} \to \infty} 1 - \theta^* = 1 - (1-\tau) \cdot \frac{\varepsilon_{D,x}}{\varepsilon_{D,p}}. \tag{16}$$

In this instance, the platform's costs that are proportional to its revenue, and the ratio of demand elasticities determines the commission rate. The logic is that if rider demand is more sensitive to waiting times than price, then commission rates are kept high to incentivize drivers to provide capacity on the platform. The platform can still charge commission without any monopsony power because it must recoup costs and wages are not monotonically increasing in the commission rate. In subsection 3.1, I show that the commission rate implied by equation (16) maximizes the wage rate when there is perfect competition for riders.

The optimal markup condition in equation (8) embodies the “seesaw” principal (Rochet and Tirole, 2006). That is, under certain circumstances, the markup that riders face can fall when the platform’s monopsony power over drivers increases. This is the case if $\varepsilon_{D,p} - \varepsilon_{D,x} < 1$, which ensures that the sensitivity of equilibrium utilization to price decreases when the platform’s monopsony power increases (*i.e.*, $\frac{d\varepsilon_{x,p}}{d\varepsilon_{H,w}} > 0$). Intuitively, when this holds, a reduction in price increases utilization by less so that waiting times do not increase as much and, as a result, there is higher demand than otherwise, which encourages further price reductions.

The model also yields an augmented inverse elasticity pricing rule. If the platform faces a perfectly competitive market for drivers, then the optimal markup is given by

$$\lim_{\varepsilon_{H,w} \to \infty} \mu^* = \frac{1}{\varepsilon_{D,p} - \varepsilon_{D,x}}. \tag{17}$$

This combines the traditional pricing motivation of a monopolistic firm in a one-sided environment with an additional two-sided market concern. That is, increasing prices reduces utilization which partially offsets the fall in demand and, therefore, justifies a higher markup from a profit-maximizing perspective.

Lastly, when monopsony power is extreme but the market for riders is competitive, introducing some competition for drivers will have a negligible affect on the platform’s markup while reducing the commission rate. Formally, the elasticity of μ^* under perfect competition for riders with respect to $\varepsilon_{H,w}$ is

$$-\frac{\varepsilon_{H,w} \cdot (1-\kappa)}{1 + \varepsilon_{H,w} \cdot (1-\kappa)}, \tag{18}$$

which equals zero when $\varepsilon_{H,w}$ is evaluated at zero. Conversely, the elasticity of θ^* in the same scenario with respect to $\varepsilon_{H,w}$ is $\frac{1}{1+\varepsilon_{H,w}}$, which equals one when $\varepsilon_{H,w}$ is zero. Practically, this suggests that encouraging more competition for drivers’ services should not negatively impact rider welfare when starting from an extremely monopsonistic situation.

2.3 Discussion

This subsection discusses several aspects of the model outlined above.

Measuring hours. The labor supply function $H(w)$ describes the number of hours worked by drivers on the platform. In practice, measuring labor supply to a particular platform is very difficult. This is because platforms observe the time when workers are "online" which, broadly speaking, measures the hours drivers are logged into a particular platform. However online status is costless to maintain because it does not obligate individuals to do anything. For example, drivers can be at home with no intention of accepting jobs but still appear online or, worse, they may be working for a competing platform.

The concept of hours in this paper corresponds to a metric of labor supply which translates into rides via utilization and reduced waiting times consistently. In other words, it is a structural measure of *genuine* labor supply which the platform can rely on to serve the marketplace. Note that the platform does not need to observe this measure to price optimally. Instead, they can experiment to reach their optimal pricing structure. Therefore, this approach offers a way to circumvent the issue of directly observing labor supply since driver supply elasticities can be inferred from platform behavior.

Pricing. The model assumes that the platform enforces a constant price and commission rate. Of course, this is equivalent to setting two different prices for drivers and riders but, given that platforms typically employ commission rates, the setup provides a convenient mapping to reality. However, platform prices and commission rates may be state-dependent. Unfortunately, the algorithms that determine these pricing decisions, as well as the data required to understand exactly how they manifest, are proprietary and only available at the behest of platforms.

Rather than accounting for the intricacies of pricing strategies, this model aims to provide a bird's-eye view of platform behavior that is informative of platform market power with minimal data requirements. This is particularly useful if platforms use a bracketing heuristic to make decisions. In other words, platforms set baseline prices and commission rates to maximize profits and then subsequently finesse their state-dependent pricing. The fact that the ratio of revenue to gross bookings in Uber's public financial filings has been so constant, as well as public comments by the platform's

CEO,[7] suggests that this is approximately the case.

Time-varying demand. Relatedly, in the model, demand is static and deterministic but, in reality, platforms have to deal with fluctuating demand levels. This challenge is often met with state-dependent pricing. Again, the goal of this model is to provide a bird's-eye view of this marketplace rather than to offer insights into these details. To the extent that a platform faces varying demand but sets a constant price and commission rate, the solution to the platform's problem, which equations (4) and (5) describe, can be seen as the solution to a stochastic version of this problem as long as any shocks enter the platform's objective function linearly. For example, a multiplicative shock to demand would satisfy this requirement.

Platform costs. I model platforms as facing a variable cost for mediating exchanges between buyers and sellers. As discussed in more detail later, this feature can reflect transaction costs and taxes *etc.* In addition to these costs, platforms face fixed costs and, potentially, costs in attracting and maintaining riders and drivers on the platform (Manning, 2006). Given the digital nature of most platforms under consideration, these latter costs should be subsumed into a platform's fixed cost. For example, the same software facilitates all drivers' onboarding procedures, and riders' details are stored on the same server, where there marginal cost of storage is minimal. Moreover, advertising campaigns to attract new drivers and passengers are part of a fixed marketing budget.

Theoretically, fixed costs should not influence optimal pricing, which concerns the trade-off between marginal revenue and marginal costs. But, if these expenses comprise the bulk of a platform's overall costs, it is plausible that they do affect the pricing decision. Most likely this will be through some reservation profit share for mediating exchanges, which can be incorporated into the model via higher than otherwise marginal mediation costs.

3 Redesigning the Marketplace

[7] Uber's CEO, Dara Khosrowshahi, has said, "[the platform] optimizes for an average take-rate". See the interview with The Rideshare Guy here.

3.1 Unionization and Commission Caps

This subsection assesses the impact of commission caps on equilibrium outcomes. I assume that the commission rate is set by an organization, such as a union, to maximize worker welfare. The platform then takes account of this new commission rate and re-optimizes its pricing. The analysis shows that, when the platform faces a competitive market for riders, this market design leads to a commission rate that coincides with social planner's in equation (15). In response, the platform raises prices, which further reduces waiting times and partially compensates riders.

To clarify timing: in period one, the commission rate is set to maximize worker welfare; in period two, the platform sets its price; and in period three, the market's participants make their decisions taking the commission rate and price as given, and outcomes are realized. I solve this game using backward induction. In period three, rider and driver behavior is fully described by the functions $D(\bullet)$ and $H(\bullet)$, respectively. In period two, the platform takes the commission rate as given and sets the price according to their first order condition, which is described by equation (4).

In period one, the commission rate is set to maximize worker welfare. Under the assumption of an isoelastic labor supply curve, this is equivalent to maximizing the wage rate. The optimization problem is subject to two constraints. Firstly, utilization will respond to bring the market to equilibrium, which will also affect wages. Secondly, it is necessary to internalize the fact that the platform will adjust prices in response to changes in the commission rate. I summarize the platform's best response function with the notation $P(\theta)$. Formally, the problem can be written down as

$$\max_{\theta} \; p \cdot \theta \cdot x \;\text{ subject to }\; p = P(\theta) \;\text{ and }\; D(p, x) = x \cdot H(p \cdot \theta \cdot x), \tag{19}$$

which yields the first-order condition

$$1 + \varepsilon_{P,\theta} - \varepsilon_{x,\theta} = 0, \tag{20}$$

where $\varepsilon_{P,\theta} = \frac{\partial P(\bullet)}{\partial \theta} \cdot \frac{\theta}{P(\bullet)}$. The definition of $\varepsilon_{x,\theta}$ remains the same but the expression differs from equation (6) because of the different market design. Now, this elasticity equals

$$\varepsilon_{x,\theta} = \frac{\varepsilon_{D,p} \cdot \varepsilon_{P,\theta} + \varepsilon_{H,w} \cdot (1 + \varepsilon_{P,\theta})}{\varepsilon_{D,x} + 1 + \varepsilon_{H,w}}. \tag{21}$$

Moreover, the platform's optimal choice of price in equation (4) implies that

$$\varepsilon_{P,\theta} = \frac{\theta}{1-\theta-\tau}. \tag{22}$$

Theorem 3 (The union's commission rate.)**.** *The commission rate that maximizes drivers' wages is*

$$1-\theta^{**} = 1-(1-\tau)\cdot\frac{1+\varepsilon_{D,x}}{\varepsilon_{D,p}}. \tag{23}$$

Proof. This follows from plugging equations (21) and (22) into equation (20). □

Comparing this condition to equation (9) reveals that the wage maximizing commission rate is necessarily lower than the level set by a monopsonistic platform. Given that the socially efficient commission rate (15) is also lower than the platform's preference, the wage maximizing commission rate is closer to the socially efficient level. In fact, they are equal when the rider market is perfectly competitive.

This provides a rationale for allowing workers to unionize and set the commission rate because it can restore the commission rate to the social planner's desired level. However, prices would still be in the hands of the platform and not at their corresponding first-best level. Consequently, although driver welfare would undoubtedly improve, the impact on overall welfare is ambiguous. Previewing later results that suggest the market for riders is very competitive and, hence, the rider surplus is close to zero, I focus on driver welfare below.

3.2 Wages and Driver Welfare

Under the assumption of an isoelastic labor supply function, drivers' surplus in this market equals

$$U(w) = \frac{w\cdot H(w)}{1+\varepsilon_{H,w}}. \tag{24}$$

Worker welfare is monotonic in wages, and changes in the commission rate translate to worker welfare via the level of wages and the number of hours worked on the platform. The change in welfare due to an exogenous change in the commission rate, which is of primary interest in the counterfactual below, is given by

$$\varepsilon_{U,\theta} = (1+\varepsilon_{H,w})\cdot\varepsilon_{w,\theta}, \tag{25}$$

where $\varepsilon_{U,\theta} = \frac{dU}{d\theta} \cdot \frac{\theta}{U}$.

Changing the rate of commission affects wages in three ways, as shown by the elasticity of wages to the commission rate

$$\varepsilon_{w,\theta} = 1 + (1 - \varepsilon_{x,p}) \cdot \varepsilon_{P,\theta} - \varepsilon_{x,\theta}, \tag{26}$$

where $\varepsilon_{w,\theta} = \frac{dw}{d\theta} \cdot \frac{\theta}{w}$. Firstly, reducing the commission rate mechanically increases wages as workers keep a larger share of revenue. Secondly, it causes an increase in prices due to the platform's behavioral response. This effect can increase or decrease wages because higher prices mechanically raise wages but they also lead to a drop in utilization, which can outweigh the mechanical effect. Thirdly, higher commission rates encourage higher driver supply, which leads to lower utilization and, in turn, lower wages.

4 An Application to Uber

In this section, I use the theory from section 2 to evaluate the extent of monopsony power enjoyed by the US's largest rideshare platform, Uber. This is possible using only publicly available data because of the model's parsimonious structure. The results suggest that Uber prices as if enjoying a substantial amount of monopsony power over drivers while experiencing a very competitive market for riders. However, the impact of monopsony power on wages is attenuated relative to a traditional wage-posting model because of equilibrium responses in utilization. In the end, driver wages are held down by seven percent compared to the socially efficient benchmark.

4.1 Institutional Details

Uber was founded in 2009 and has grown to operate in 72 countries globally. It is the largest ridesharing platform in the US with an estimated market share of around 70 percent. Currently, Uber has 1.5 million earners on its platform in the US. For most areas in the US, workers are free to join and leave the platform and, once on the platform, drivers pick where and when to work. Moreover, drivers can work simultaneously for Uber's competitors like Lyft.

Given the available data, the focus of the analysis in this paper is early 2017 in the US. During this time, passenger fares were determined by time and distance, as well as Uber's surge algorithm. Of this fare, the platform received 20 percent through an

Uber fee. Some additional share of the fare was used to directly cover costs in the form of booking and service fees such that drivers often received less than 80 percent of the rider fare. These factors culminated in an overall commission rate greater than the Uber fee, which is discussed below.

4.2 Data

Estimation requires three empirical moments to identify the model's three structural parameters: $\varepsilon_{D,p}$, $\varepsilon_{D,x}$, and $\varepsilon_{H,w}$. Uber's commission rate (*i.e.*, $\widehat{1-\theta}$) provides the first empirical moment. This number is the subject of public discussion and is occasionally reported by drivers who publicize their service fee summaries. Better than this, the commission rate has also been reported using proprietary microdata in several academic publications (Caldwell and Oehlsen, 2021; Castillo, 2020). Following these studies, which consider Houston in 2017, the benchmark commission rate in the estimation is 26 percent. I also consider commission rates of 30 percent and 22 percent. As well as reflecting some uncertainty about the true value of the commission rate, these numbers are also indicative of where Uber's commission rate used to be before 2017, when the platform was more generous to drivers, and where the commission rate is suggested to be at present after recent pricing changes.

Information on Uber's costs provides the second empirical moment via the implied markup $\hat{\mu}$. In particular, the main marginal costs to mediating exchanges are transaction fees for the processing of payments, sales tax payable to local government, and insurance coverage for drivers against "life-changing events". The latter element is roughly paid by the mile which is a strong determinant of a ride's price and, thus, the cost can be calculated as proportional to price.[8] Estimates of average ride distance and price, as well as insurance premiums, suggest that this cost comprises roughly 12 percent of fares. Taking numbers from Castillo (2020), transaction fees and sales tax make up three percent of the fare. This implies that on average 15 percent of the passenger fare is equal to the cost that Uber experiences from mediating the exchange. To examine the sensitivity of estimates to uncertainty in this calculation, I also consider total costs equivalent to 12 percent and 18 percent of the fare.

The third and final empirical moment is the equilibrium response of utilization to a change in price.[9] Hall et al. (2023) report static and dynamic estimates of this statis-

[8] Importantly, this cost does not remain proportional to the fare in counterfactuals.

[9] The equilibrium response of utilization to a change in the commission rate would provide an overidentifying restriction but, unfortunately, I am not aware of any estimates of this statistic.

tic, which exploit pricing experiments by the platform. Given that pricing is driven by long-term considerations, I use the dynamic estimate, which is six months out from the price change, and its standard error from Figure 5 in the paper. I infer a central estimate of 1.40 with a standard error of 0.38 (= 0.75/1.96). This estimate is from several large US cities between 2014 and 2017.

The measure of utilization in this empirical moment uses online hours in the denominator, which differs from the relevant concept of *genuine* labor supply. To correct for this, I leverage the structure of the model to adjust the measure of utilization during the estimation. This makes use of a further moment that is reported in Hall et al. (2023), namely, the elasticity of online hours to earnings $\hat{\varepsilon}_{H,w}$ and the following Taylor series approximation

$$\varepsilon_{x,p} \approx \hat{\varepsilon}_{x,p} + \frac{\partial \varepsilon_{x,p}}{\partial \varepsilon_{H,w}} \cdot (\varepsilon_{H,w} - \hat{\varepsilon}_{H,w}) = \hat{\hat{\varepsilon}}_{x,p}, \qquad (27)$$
$$\text{where} \quad \frac{\partial \varepsilon_{x,p}}{\partial \varepsilon_{H,w}} = \frac{1 - (\varepsilon_{D,p} - \varepsilon_{D,x})}{(\varepsilon_{D,x} + 1 + \varepsilon_{H,w})^2}.$$

So $\hat{\hat{\varepsilon}}_{x,p}$ is used as the third empirical moment in the estimation. In practice, this does not impact estimates noticeably.

For the version of the model that incorporates Uber's surge pricing, which is presented in appendix A, an additional empirical moment is required. I use the elasticity of the surge price multiplier to price changes also from Hall et al. (2023) to pin down the equilibrium response of surge pricing to wait times via utilization.

4.3 Estimation

Generalized method of moments produces estimates of the model's structural parameters. Precisely, I select $\boldsymbol{\varepsilon} = (\varepsilon_{D,p},\ \varepsilon_{D,x},\ \varepsilon_{H,w})$ to minimize the distance between $\hat{X} = (\widehat{1-\theta},\ \hat{\mu},\ \hat{\hat{\varepsilon}}_{x,p})$ and the model's predictions using the norm $m(\hat{X}, \boldsymbol{\varepsilon})^T \cdot W \cdot m(\hat{X}, \boldsymbol{\varepsilon})$, where

$$m(\hat{X}, \boldsymbol{\varepsilon}) = \begin{pmatrix} \hat{\mu} - \frac{1+\varepsilon_{D,x}+\varepsilon_{H,w}}{\varepsilon_{D,p}+\varepsilon_{H,w}\cdot(\varepsilon_{D,p}-\varepsilon_{D,x})} \\ \widehat{(1-\theta)} - 1 - (1-\tau) \cdot \frac{\varepsilon_{D,x}}{\varepsilon_{D,p}} \cdot \frac{\varepsilon_{H,w}}{1+\varepsilon_{H,w}} \\ \hat{\hat{\varepsilon}}_{x,p} - \frac{\varepsilon_{D,p}+\varepsilon_{H,w}}{\varepsilon_{D,x}+1+\varepsilon_{H,w}} \end{pmatrix}, \qquad (28)$$

	Data moment	Model prediction
Commission rate	0.26	0.26
Markup ratio	0.42	0.42
Utilization elasticity	[0.65, 2.15]	1.18

Table 1: Model Fit

and W is the weighting matrix. I specify this as a diagonal matrix, where each element is the inverse of the empirical moments' variance, respectively. Without any standard error estimates for the commission rate and markup, I weigh these as if they had a standard error of 0.02.

I produce standard errors for the estimates by sampling 500 values of $\hat{\varepsilon}_{x,p}$ from a normal distribution with a mean of 1.40 and a standard deviation equal to 0.38. Therefore, these standard errors reflect only statistical uncertainty from the empirical estimate of the elasticity of utilization to price. The sensitivity of results to the commission rate and markup is checked by re-estimating the parameters under different assumptions about these moments.

Table 1 compares the model's predictions with the baseline empirical moments. The model fits the three data moments extremely well. Although this is unsurprising since the model is exactly identified, it is not completely trivial because of sign restrictions on the elasticities. Further, other more complex structural models have not been able to reconcile Uber's behavior with profit maximization.[10]

4.4 Results

Table 2 shows parameter estimates for nine different combinations of Uber's commission rate and costs. All of these variations find that Uber faces a very competitive market for riders (*i.e.*, high values of $\varepsilon_{D,p}$ and $\varepsilon_{D,x}$) so, for ease of interpretation, I report the adjusted ratio of the elasticity of demand to utilization and price (*i.e.*, $(1-\tau)\cdot\frac{\varepsilon_{D,x}}{\varepsilon_{D,p}}$), which I denote with $\frac{\widetilde{\varepsilon_{D,x}}}{\varepsilon_{D,p}}$. This equals one minus the commission rate under a perfectly competitive driver market. The fact that all these ratios equal one

[10]This is likely because these papers use short-term elasticities that exploit variation in surge pricing, or experiments that last less than a few weeks, to compute passenger and driver behavioral responses. As a result, these agents are very inelastic, which suggests that Uber has a lot of market power and, therefore, should charge higher prices. However, short-term elasticities are not relevant to Uber's long-term pricing decisions.

		Commission rate		
		30%	26%	22%
Costs	12%	$\frac{\varepsilon_{\tilde{D},x}}{\varepsilon_{D,p}} = 0.88$ (<0.01)	$\frac{\varepsilon_{\tilde{D},x}}{\varepsilon_{D,p}} = 0.88$ (<0.01)	$\frac{\varepsilon_{\tilde{D},x}}{\varepsilon_{D,p}} = 0.88$ (<0.01)
		$\varepsilon_{H,w} = 3.88$ (0.01)	$\varepsilon_{H,w} = 5.27$ (0.02)	$\varepsilon_{H,w} = 7.78$ (0.03)
	15%	$\frac{\varepsilon_{\tilde{D},x}}{\varepsilon_{D,p}} = 0.85$ (<0.01)	$\boldsymbol{\frac{\varepsilon_{\tilde{D},x}}{\varepsilon_{D,p}} = 0.84}$ **(<0.01)**	$\frac{\varepsilon_{\tilde{D},x}}{\varepsilon_{D,p}} = 0.84$ (<0.01)
		$\varepsilon_{H,w} = 4.66$ (0.02)	$\boldsymbol{\varepsilon_{H,w} = 6.71}$ **(0.03)**	$\varepsilon_{H,w} = 11.11$ (0.06)
	18%	$\frac{\varepsilon_{\tilde{D},x}}{\varepsilon_{D,p}} = 0.82$ (<0.01)	$\frac{\varepsilon_{\tilde{D},x}}{\varepsilon_{D,p}} = 0.82$ (<0.01)	$\frac{\varepsilon_{\tilde{D},x}}{\varepsilon_{D,p}} = 0.82$ (<0.01)
		$\varepsilon_{H,w} = 5.82$ (0.03)	$\varepsilon_{H,w} = 9.23$ (0.05)	$\varepsilon_{H,w} = 19.44$ (0.13)

Table 2: Parameter Estimates

minus the total proportional cost under consideration confirms the highly competitive rider market; the commission rate would only cover costs were it not for the platform's ability to markup thanks to monopsony power.

In contrast, the results suggest that Uber exerts significant market power over drivers. The central estimate, which is highlighted in bold at the center of table 2, implies that the platform faces a driver supply elasticity of 6.71. This number decreases if the platform is considered to charge a higher commission rate and rises if Uber is believed to face higher costs. Taking an extreme, the estimates indicate that the driver supply elasticity to Uber could be as low as 3.88. The highest estimate of the driver supply elasticity is 19.44, however, this requires a commission rate of 22 percent, which has not been offered to drivers since the platform's earliest days.

The difference between the commission rate at the top of the columns and $1 - \frac{\varepsilon_{\tilde{D},x}}{\varepsilon_{D,p}}$ in table 2 reveals how platforms use their monopsony power to markup the commission under these different scenarios. In the central scenario, the commission rate is ten percentage points higher than what would occur in the competitive labor market benchmark. An extreme estimate with a 30 percent commission rate and 12 percent proportional costs, suggests that commission rates may be 18 percentage points above the first-best.

In a standard model of wage-posting by a monopsonistic employer, the driver supply elasticities map directly to a wage markdown of $1/(1 + \varepsilon_{H,w})$. For the central estimate, this implies that workers would be denied 13 percent of their marginal product.

		Commission rate		
		30%	26%	22%
	12%	$\%\Delta w = 18$ $\%\Delta U = 85$	$\%\Delta w = 12$ $\%\Delta U = 72$	$\%\Delta w = 7$ $\%\Delta U = 58$
Costs	15%	$\%\Delta w = 13$ $\%\Delta U = 71$	$\%\boldsymbol{\Delta}\mathbf{w} = \mathbf{7}$ $\%\boldsymbol{\Delta}\mathbf{U} = \mathbf{57}$	$\%\Delta w = 3$ $\%\Delta U = 40$
	18%	$\%\Delta w = 8$ $\%\Delta U = 57$	$\%\Delta w = 4$ $\%\Delta U = 41$	$\%\Delta w = 1$ $\%\Delta U = 23$

Table 3: Welfare Effects of a Commission Cap

In the two-sided market described in section 2, this is not the case because equilibrium adjustments in utilization determine wages.

4.5 Counterfactual

This subsection aims to understand how monopsony power affects wages and, in turn, worker welfare in a two-sided ridesharing market. To do so, it is necessary to formulate a precise counterfactual. Motivated by the theoretical result that the wage maximizing commission rate equals the first-best under perfect competition for riders, which approximately holds in the case of Uber, I consider setting θ equal to $\frac{\varepsilon_{\tilde{D},x}}{\varepsilon_{D,p}}$ and leaving all else constant. Therefore, this could constitute a counterfactual where we let drivers collectively set the commission rate. An additional advantage of this formulation is that it leaves the denominator in the welfare expression (24) constant, and the platform's pricing adjustment is straightforward.

Using equations (25) and (26), table 3 presents estimates of the impact of monopsony power on wages and welfare. The central estimate in bold implies that the platform uses its monopoly power to raise commission rates above the competitive benchmark, which causes drivers to experience wages that are seven percent lower than otherwise. It is possible to decompose this reduction in wages using equation

(26) as follows

$$\%\Delta w = \left[1 + \underbrace{(1-\varepsilon_{x,p}) \cdot \varepsilon_{P,\theta}}_{\text{(1-1.18)}\times 2.85=\text{-0.50}} - \underbrace{\varepsilon_{x,\theta}}_{\sim 0}\right] \cdot \underbrace{\%\Delta\theta}_{0.15} \approx 7. \tag{29}$$

Pricing responses by the platform and equilibrium adjustments in utilization mediate the effect of changes in the commission rate on wages. The elasticity of the platform's price to the driver's keep rate is 2.85, as computed from equation (22). This has a further positive effect on drivers' wages *ceteris paribus.* However, the increase in prices also triggers an equilibrium adjustment in utilization. This equilibrium response outweighs the positive effect on wages from the platform raising prices because $1 - \varepsilon_{x,p}$ is negative. Reducing commission rates also decreases utilization further, although the impact of this is approximately zero because the rider market is so much more competitive than the driver market.

The range of wage effects varies predictably with the extent of the platform's monopsony power. The highest estimate implies that wages are almost one-fifth below their competitive equivalent. At the lower end, wages are only minimally affected by a small amount of monopsony power but, again, this requires a low level of commission that Uber no longer offers drivers. Taken together, the evidence suggests that the platform materially depresses wages below their competitive benchmark. However, these estimates are significantly lower than other papers that combine short-term variation in driver earnings to estimate supply elasticities with traditional wage-posting models (Caldwell and Oehlsen, 2021).

Table 3 also reports the overall effect on worker welfare of these wage changes, which rely on the strong assumption of an isoelastic driver supply function. This counterfactual leads to very large welfare gains for workers. A seven percent increase in wages raises worker welfare by over 50 percent. This is because the increase in wages raises the value of all the hours drivers are already working and driver supply is still moderately elastic to the wage rate, which means (new) drivers work additional hours that generate further welfare gains.

5 Conclusion

This paper develops a tractable model of a two-sided ridesharing market. The framework reveals how platforms exploit monopsony power over drivers by marking up commission rates according to the driver supply elasticity that they face. Consequently, descriptions of firm-specific labor supply functions remain an appropriate way to measure monopsony power in these settings. However, the nature of two-sided markets complicates the final effect on workers' wages and welfare. Redesigning these markets can restore efficiency in the presence of monopsony power provided the other side of the market is sufficiently competitive. In particular, allowing a union of workers to set the commission rate while preserving the platform's power to set prices delivers socially efficient pricing.

Taking the theory to the data using publicly available information on Uber's pricing and costs suggests that the US's largest ridesharing platform enjoys substantial monopsony power over workers. Because the platform faces a competitive market for riders, a worker-set commission rate would yield a first-best outcome. If this were the case, commission rates would fall by 10 percentage points, wages would increase by seven percent, and worker welfare would increase dramatically.

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Appendices

In Progress

A Theory with Surge Multiplier

I write prices as a multiplicative function of a base price b and an average surge multiplier m. To capture the role of surge multipliers in helping to equate supply and demand, the average multiplier depends on the utilization rate $m = M(x)$. Therefore, riders face a price

$$p = M(x) \cdot b. \tag{30}$$

Platforms select a base price and commission rate while taking the surge pricing algorithm as given. Formally, platforms face the following problem

$$\max_{b,\theta} \big[p \cdot (1-\theta) - c\big] \cdot D(p, x) \text{ subject to } D(p, x) = x \cdot H(p \cdot \theta \cdot x) \quad \text{and } p = M(x) \cdot b, \tag{31}$$

where c is the cost of mediating one hour of transportation. In words, the platform seeks to maximize revenue over costs but they are constrained by the equilibrium adjustment of driver utilization and surge algorithms. Platform optimization yields two first-order conditions b and θ, respectively,

$$(1 - \varepsilon_{M,b}) + \mu \cdot \big(\varepsilon_{D,x} \cdot \varepsilon_{x,b} - \varepsilon_{D,p} \cdot (1 - \varepsilon_{M,b})\big) = 0, \tag{32}$$

$$-\varepsilon_{M,x} \cdot \varepsilon_{x,\theta} - \frac{\theta}{1-\theta} + \mu \cdot (\varepsilon_{D,p} \cdot \varepsilon_{M,x} \cdot \varepsilon_{x,\theta} + \varepsilon_{D,x} \cdot \varepsilon_{x,\theta}) = 0, \tag{33}$$

where $\varepsilon_{M,x} = \frac{\partial M(\bullet)}{\partial x} \cdot \frac{x}{M(\bullet)}$, $\varepsilon_{M,b} = -\frac{dM(\bullet)}{db} \cdot \frac{b}{M(\bullet)}$, $\varepsilon_{D,x} = -\frac{\partial D(\bullet)}{\partial x} \cdot \frac{x}{D(\bullet)}$, $\varepsilon_{D,p} = -\frac{\partial D(\bullet)}{\partial b} \cdot \frac{p}{D(\bullet)}$, $\varepsilon_{x,b} = -\frac{dx}{db} \cdot \frac{b}{x}$, $\varepsilon_{x,\theta} = -\frac{dx}{d\theta} \cdot \frac{\theta}{x}$, and $\mu = \frac{p\cdot(1-\theta)-c}{p\cdot(1-\theta)}$. Comparative statics on the market-clearing condition provide two more equalities that connect all the relevant elasticities

$$\varepsilon_{x,b} = \frac{(\varepsilon_{D,p} + \varepsilon_{H,w}) \cdot (1 - \varepsilon_{M,b})}{\varepsilon_{D,x} + 1 + \varepsilon_{H,w}}, \tag{34}$$

$$\varepsilon_{x,\theta} = \frac{\varepsilon_{H,w}}{\varepsilon_{D,p} \cdot \varepsilon_{M,x} + \varepsilon_{D,x} + 1 + \varepsilon_{H,w} + \varepsilon_{H,w} \cdot \varepsilon_{M,x}}, \tag{35}$$

	Data moment	Model prediction
Commission rate	0.26	0.26
Markup ratio	0.42	0.42
Utilization elasticity	[0.84, 3.16]	1.18
Surge elasticity	[0.02, 0.41]	0.21

Table A1: Model Fit with Surge Multiplier

where $\varepsilon_{H,w} = \frac{\partial H(\bullet)}{\partial w} \cdot \frac{w}{H(\bullet)}$. These can be inserted into the first-order conditions (32) and (5) to produce

$$\mu = \frac{1 + \varepsilon_{D,x} + \varepsilon_{H,w}}{\varepsilon_{D,p} + \varepsilon_{H,w} \cdot (\varepsilon_{D,p} - \varepsilon_{D,x})}, \tag{36}$$

$$\frac{1-\theta}{\theta} = \frac{\varepsilon_{H,w}^{-1} \cdot (1 + \varepsilon_{D,p} \cdot \varepsilon_{M,x} + \varepsilon_{D,x}) + 1 + \varepsilon_{M,x}}{\mu \cdot (\varepsilon_{D,x} + \varepsilon_{D,p} \cdot \varepsilon_{M,x}) - \varepsilon_{M,x}}. \tag{37}$$

B Decntralized Pricing