Monopsony Power in the Gig Economy

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Preliminary: comments are welcome.

Abstract

Many workers provide services for customers via platforms that may exert monopsony power. Typical expositions of this phenomenon are inapplicable because platforms post prices, rather than wages, to both sides of a two-sided market. Further, platform-specific labor supply is hard to measure. This paper develops a model of a ridesharing gig market that explicitly incorporates these issues. Intermediaries exploit monopsony power to markup commission and reduce equilibrium wages. A driver union sets the first-best commission rate when the passenger market is competitive. Estimating the model with public data on Uber suggests this is relevant; the platform faces competition for passengers but leverages monopsony power to depress wages by 14 percent. First-best commission rates increase the welfare of Uber's 1.5 million US drivers by 20 percent. Conversely, minimum wages on utilized hours fail to benefit workers.

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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 (Jullien et al., 2021; 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 prices and quantities.

Yet, the rise of gig work (Garin et al., 2023), where platforms mediate exchanges between independent buyers and sellers of labor services, has pushed the economics of two-sided markets into the spotlight. 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, instead of posting wages, set prices for customers and commission rates for workers?[1] And how can monopsony power be addressed in this context?

This paper develops a tractable model to study a typical and important two-sided gig market: ridesharing. The model provides clear insights into the motivations behind platform pricing, as well as the merits of alternative market designs and platform competition. Further, given the model's parsimonious structure, only a small number of sufficient statistics are required for estimation. I demonstrate the framework's utility by using it to evaluate the extent of market power enjoyed by the US's largest ridesharing platform, Uber, with publicly available data. From a policy perspective, this paper offers a transparent and workable tool to investigate gig labor markets.

The results suggest that Uber wields substantial monopsony power over drivers but faces strong competition for riders. Consequently, commission rates are 15 percentage points higher than relative to a competitive benchmark. This causes the platform to charge lower prices than otherwise which attenuates wage losses by raising driver utilization in equilibrium. The model reveals that setting commission rates to maximize wages (*e.g.*, by delegating this to a driver union) restores this dimension of pricing to its socially efficient level because the passenger market is sufficiently competitive. This would cause wages to rise by 14 percent relative to the *status quo*. Ac-

[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 buy labor that they then offer customers, or whether customers are the buyers and platforms only mediate exchanges. I take the former view and treat platforms as potentially having monopsony power. However, in what follows, this is only an issue of semantics.

counting for workers' other earnings, this represents a 20 percent increase in welfare for the 1.5 million Uber drivers in the US.

Concretely, I consider a ridesharing platform that operates a two-sided marketplace, and that sets the price of exchanges and the commission rate they receive. Riders on the platform care about the price they face and the utilization of drivers, which maps to waiting times. Hourly wages, which also depend on utilization, determine the supply of drivers. Importantly, the market reaches equilibrium through adjustments in worker utilization because drivers enter and exit as their wage rate moves with utilization, and riders change their demand as wait times respond accordingly. Therefore, equilibrium is defined by a fixed point where utilization equals the ratio of optimal rider demand and driver supply choices. This exposition builds upon evidence in Hall et al. (2023), which describes how rideshare markets equilibrate.

The model delivers several intuitions about decision-making by intermediaries. Platforms markup the commission rate that drivers pay when they enjoy monopsony power. 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 labor supply elasticity is still a useful measure of monopsony power in this novel context. However, it is an incomplete picture. Demand-side elasticities and a precise counterfactual, which dictates the response of prices and driver utilization, are necessary to infer the ultimate effect on wages and welfare.[2]

If a platform faces perfect competition for drivers, commission rates need not converge to zero for two reasons. First, platforms must cover their costs from mediating exchanges. Second, 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, commission rates are kept low to incentivize drivers to provide capacity. Conversely, if demand is more responsive to price, the platform would rather stimulate demand with a lower price and take a higher share of revenues from drivers.

The model yields other lessons about pricing in two-sided markets. Platforms follow a Lerner-type rule that converges to an inverse elasticity rule when there is no

[2] Product market power also has implications for monopsony power in one-sided markets too, see Kroft et al. (2020). A key difference in the two-sided setting is that there are multiple elasticities on the demand side (*e.g.*, prices and waiting times) because of network effects and different equilibrium mechanics.

monopsony power (Lerner, 1934; Rochet and Tirole, 2006). In this case, the Lerner index should equal the inverse of the difference between the price elasticity and utilization elasticity of rider demand. This reflects a trade-off between the behavioral and mechanical effects of a price change alongside the fact that higher prices reduce waiting times through utilization, which offsets the decline in demand. The model also exhibits the "seesaw" principle (Rochet and Tirole, 2003), whereby changes in market fundamentals benefit one side of the market and hurt the other. For example, an increase in platform monopsony power raises commission rates but, if passengers are sufficiently sensitive to waiting times, reduces passenger fares.

Platform competition is desirable in the ridesharing context: the platform's optimal price and commission rate coincide with the social planner's when the platform has no market power (*i.e.*, the behavioral elasticities approach infinity). This result is in contrast to ambiguous results in the literature (Hagiu and Jullien, 2014; Tan and Zhou, 2021), and is due to two features of the model. First, network effects are determined by the ratio of participation on either side of the market, not the product (Weyl, 2010). Second, waiting times depend only on utilization so that fragmenting participants across different platforms is not consequential if the utilization rate is preserved, which can be interpreted as a multi-homing assumption.

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, there are 1.5 million drivers actively working on the platform and over 6 million globally. Moreover, despite evidence that many workers benefit substantially from the opportunity to partake in ridesharing markets and alike (Fisher, 2022), concerns remain about the welfare of individuals subject to these work arrangements (Prassl, 2018; Ravenelle, 2019). One reason for this anxiety is a fear that platforms use monopsony power to benefit at the expense of drivers.

Platforms may wield market power over workers for several reasons. For example, workers could have unattractive outside options due to underemployment (Lachowska et al., 2023), and gig work entails a unique bundle of amenities that other jobs cannot offer (*e.g.*, flexible hours, see Chen et al. (2019)). In addition, many labor market regulations that remedy imbalances of bargaining power between employers and employees do not apply in the gig economy. To compound this, platforms benefit from network effects while interacting with marketplace participants in an opaque way. For example, drivers are not allowed to ask passengers the fare they are paying.

Given the above, 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 challenging for at least three reasons. First, as discussed, gig platforms operate two-sided marketplaces so the usual approaches to estimating monopsony power do not apply. Second, 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.

Third, drivers' labor supply is hard to measure (Harris and Krueger, 2015; Hyman et al., 2020). Intermediaries 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-homing across platforms 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 gig labor markets. I circumvent this issue by inferring a genuine driver supply elasticity from platforms' pricing decisions. This does not require platforms to observe a measure of genuine labor supply either, 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 avail-

[3] There are notable efforts to scrape data on ridesharing and related markets, for example, see Rosaia (2020). Efforts like the EU's Data Act may also be one way to avoid this issue.

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

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

able 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 in collaboration with Uber. Given the evidence available, this study focuses on Uber's US rideshare marketplace in the years around 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 or 25 percent fee that Uber publicizes because some of the fare, known as the booking fee, is earmarked to cover costs. Using proprietary data reported in Castillo (2023) and Cook et al. (2021) (and their earlier working paper versions), I calculate a commission rate of 34 percent. Anecdotal evidence from service fee summaries provided by Uber to drivers, as well as driver discussions in online fora, is also consistent with these numbers. Notably, Uber's commission rate was increasing up to 2017 (Caldwell and Oehlsen, 2021), and public financial filings indicate the commission rate may have risen since.[6]

Uber's primary marginal costs for mediating exchanges are transaction fees for processing payments, sales tax payable, and commercial auto-insurance for drivers. Again, Castillo (2023) reports that the first two costs constitute three percent of the fare in Houston, Texas for 2017. Estimates of the average fare, average distance to pickup and average trip distance from Cook et al. (2021), and per-mile insurance costs imply that insurance premiums comprise just over 15 percent of any fare. Therefore, in total, 18 percent of the fare equals the cost to Uber of facilitating the exchange. I consider a range of values for the platform's commission rate and costs to deal with uncertainty in these numbers. Further, high fixed cost businesses may price as if they have greater marginal costs to cover the former.

The final moment to identify the model 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% price increase, utilization eventually falls by 14%. This response is measured almost six months after the treatment was introduced and so is informative of the *long-run* behavioral elasticities that drive base pricing decisions, rather than short-run phenomena that pertain to surge pricing. Since the decrease in utilization exceeds the increase in prices, this evidence suggests that fare rises reduce wages. I account for the statistical uncertainty stemming from this moment in the estimation.

[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, although accounting practices make this hard to interpret.

Bringing the model to the data, the results suggest that Uber faces strong competition 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 4.27.[7] Viewed through the model, this implies a 15 percentage point markup of the commission rate relative to the competitive benchmark which, in standard wage-posting models, corresponds to a wage markdown of almost one-fifth. But this is not the case in a two-sided market, where rider prices and utilization will also change in equilibrium.

Therefore, it is necessary to consider a precise counterfactual to understand the impact of monopsony power on wages and 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, which provides a formal motivation for commission caps in multi-sided markets (Sullivan, 2022). Since this is estimated to be the case for Uber, I study setting the commission rate to the first-best level while leaving all the behavioral elasticities constant. In turn, the platform responds with changes to its price setting and the marketplace equilibrates through utilization. This counterfactual is practically feasible; it could be achieved by allowing drivers to unionize with the power to set commission rates.

In this scenario, a commission rate fall of 15 percentage points triggers the platform to raise prices by almost half. In turn, this causes utilization to fall by over half so that, overall, wages rise by 14 percent. This prediction differs significantly from a one-sided model of monopsony power, and demonstrates the importance of accounting for two-sidedness. Still, the wage gains precipitate a 74 percent increase in driver surplus from the marketplace. Accounting for gig work's share of participants overall income, this implies a 20 percent increase in worker welfare, which suggests monopsony power poses a major hurdle to unlocking the potential of the gig work.

Lastly, I derive conditions under which a minimum wage on utilized hours increases equilibrium wages, which is the welfare-relevant quantity. The condition depends on the ratio of mediation costs to the imposed minimum and demand elasticities, but not driver behavior. This type of minimum wage is unlikely to benefit most workers because the average utilized wage is already high at $28.96 so raising it meaningfully causes the platform to reduce equilibrium wages. Intuitively, the platform's monopsony power manifests in low utilization rates that lead to a much lower equilibrium wage of $14.71—and a minimum wage on utilized hours fails to address this.

[7] This number is close to estimates found across US labor markets in Lamadon et al. (2022).

This paper proceeds as follows: section 2 develops a model of a ridesharing market, section 3 considers alternative marketplace designs, section 4 presents the empirical application to Uber, and section 5 concludes.

2 Model of a Two-Sided Ridesharing Marketplace

This section develops a model of a two-sided ridesharing marketplace operated by a platform. The theory builds upon the framework of Hall et al. (2023) by explicitly considering the platform's price and commission rate setting. I save most discussion points 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, and the definition of equilibrium in the model.

Drivers. Ridesharing drivers decide how much to work on the platform according to the wage rate that they can earn. An aggregate driver labor supply function $H(w)$, which depends on hourly wages w, determines the number of driver hours available to the platform. The function comprises 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 rather than online hours, which do not necessarily reflect *genuine* labor supply.

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.*, the keep-rate or 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 micro-foundations. Firstly, under a constant returns-to-scale matching function between drivers and riders, waiting times are solely a function of the utilization rate and the matching technology's structural parameters (Cullen and Farronato, 2021). Hall et al. (2023) argues that this is a reasonable approximation in the context of Uber. Secondly, queuing theory finds utilization is crucial in determining waiting times, most famously in Kingman's equation (Kingman, 1961). Here, the structural parameters that determine waiting times correspond to features of the distribution of arrivals and characteristics of trips.

Equilibrium. The marketplace equilibrates through adjustments in utilization instead of price because the platform sets the latter. In particular, given a price and a commission rate, equilibrium requires that

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

In other words, utilization must satisfy a fixed point; equilibrium utilization equals the ratio of optimally chosen demand and supply of ridesharing hours, which also depend on utilization. This is analogous to the condition in Hall et al. (2023). For a given p and θ, 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.

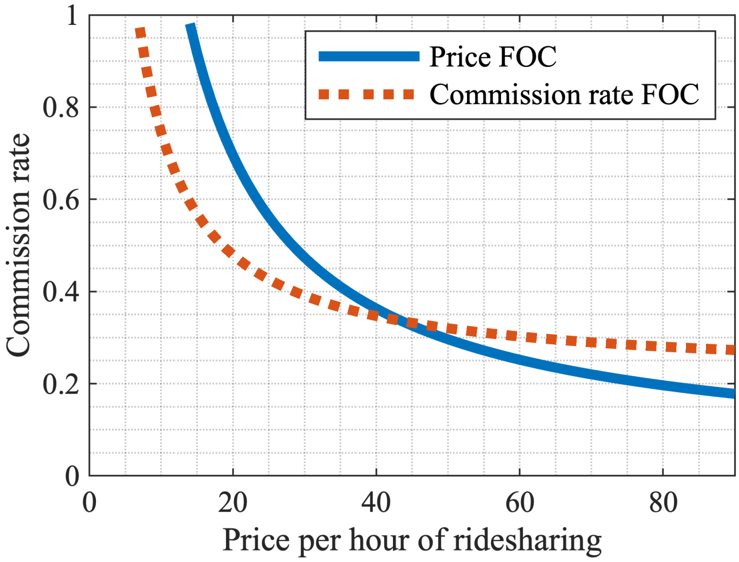
2.2 The Platform

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

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

where τ represents costs that are proportional to the fare (*e.g.*, taxes and transaction fees) and c denotes other costs of mediation (*e.g.*, insurance premiums). Platform

Figure 1: The Platform's First Order Conditions



Notes: This figure plots the platform's first-order conditions, where the behavioral elasticities and cost parameters are evaluated at the levels estimated and calibrated, respectively, in section 4.

optimization yields two first-order conditions for p and θ, respectively,

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

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

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 $\mu = \frac{p \cdot (1-\theta-\tau) - c}{p \cdot (1-\theta-\tau)}$.[8] 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 after the platform pays taxes and fees. Asterisks denote optimally chosen endogenous variables.

Equation (4) reveals 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.

[8]For ease of interpretation, I sign all elasticities to ensure that they are positive.

This paper focuses on the platform's choice of commission rate and Lerner index but, for illustrative purposes, Figure 1 plots the platform's first order conditions in terms of price per hour of ridesharing and the commission rate. These functions are obtained by rearranging equations (4) and (5), respectively, as

$$1-\theta^* = \frac{A}{1+A}\cdot\frac{c}{p^*}+\tau, \tag{6}$$

$$1-\theta^* = \frac{B}{1+B}\cdot\frac{c}{p^*}+\frac{B}{1+B}\cdot\tau+\frac{1}{1+B}, \tag{7}$$

where $A=\varepsilon_{D,x}\cdot\varepsilon_{x,p}-\varepsilon_{D,p}$ and $B=\varepsilon_{D,x}\cdot\varepsilon_{x,\theta}$. Under the parameter values shown, both lines are decreasing so that when the commission rate decreases the platform increases prices and *vice versa*. The point at which the lines cross reveals the platform's optimal commission rate and price choice.

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

$$\varepsilon_{x,p} = \frac{\varepsilon_{D,p}+\varepsilon_{H,w}}{\varepsilon_{D,x}+1+\varepsilon_{H,w}}, \tag{8}$$

$$\varepsilon_{x,\theta} = \frac{\varepsilon_{H,w}}{\varepsilon_{D,x}+1+\varepsilon_{H,w}}, \tag{9}$$

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. Intuitively, the numerator of equations (8) and (9) reflect the direct effect of their respective price and commission rate changes, while the denominators capture equilibrium effects.

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*

$$\mu^* = \frac{1+\varepsilon_{D,x}+\varepsilon_{H,w}}{\varepsilon_{D,p}+\varepsilon_{H,w}\cdot(\varepsilon_{D,p}-\varepsilon_{D,x})}, \tag{10}$$

$$1-\theta^* = 1-(1-\tau)\cdot\frac{\varepsilon_{D,x}}{\varepsilon_{D,p}}\cdot\frac{\varepsilon_{H,w}}{1+\varepsilon_{H,w}}. \tag{11}$$

Proof. Substituting equations (8) and (9) into the first-order conditions (4) and (5), and rearranging gives expressions (10) and (11). □

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 $\varepsilon_{H,w} > 0$, $\varepsilon_{D,p} > 1$, and $\varepsilon_{D,x} > 0$, which is easily satisfied in the empirical application.

2.3 The Social Planner

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

$$\max_{p,\theta} \left[p \cdot (1-\theta-\tau) - c\right] \cdot D(p,x) + \frac{p \cdot D(p,x)}{\varepsilon_{D,p} - 1} + \frac{w \cdot H(w)}{1+\varepsilon_{H,w}}$$
$$\text{subject to } D(p,x) = x \cdot H(p \cdot \theta \cdot x). \tag{12}$$

That is, 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

$$\left[p \cdot \left(\frac{\varepsilon_{D,p}}{\varepsilon_{D,p}-1} - \frac{\varepsilon_{H,w}}{1+\varepsilon_{H,w}} \cdot \theta - \tau\right) - c\right] \cdot D(p,x). \tag{13}$$

Theorem 2 (Efficient private equilibrium)**.** *The private equilibrium, which is described by equations* (10) *and* (11)*, is socially efficient if both sides of the market are perfectly competitive (i.e., all behavioral elasticities converge to infinity).*

Proof. The social planner's objective function (13) converges to the platform's profit function (3) as $\varepsilon_{D,p}$ and $\varepsilon_{H,w}$ approach infinity. □

Under perfect competition for drivers and riders (*i.e.*, all behavioral elasticities converging to infinity), the platform's pricing is first-best because the intermediary shares the same objective function and constraint as the social planner. This follows from the fact that the fractions involving behavioral elasticities in equation (13) converge to one in this situation.

This results stands in contrast to work that shows platform competition can be harmful (*e.g.*, see Frechette et al. (2019); Tan and Zhou (2021)). The key distinction in this model is that utilization (*i.e.*, the ratio, not the product, of agents on either side of the market) governs network effects and, once this is constant, changes in behavioral elasticities only effects the platform's pricing. This feature is more appealing in scenarios where market participants can multi-home and where competition comes from the threat of entry by platforms, or adaptation by customers, rather than a fracturing of agents across different platforms.

In practice, the coinciding of the platform and the social planner's objective function under perfect competition is a convenient property of a model whose purpose is to focus on the role of market power in distorting outcomes. I also note that in the empirical counterfactuals studied below I do not increase or decrease competition but rather consider alternative market designs, such as commission caps and minimum wages, to alleviate the influence of market power.

Understanding socially efficient pricing in the presence of market power requires further analysis. The social planner's 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

$$1 + \tilde{\phi} \cdot \left(\varepsilon_{D,x} \cdot \varepsilon_{x,p} - \varepsilon_{D,p}\right) + \frac{\tilde{\theta}}{\frac{\varepsilon_{D,p}}{\varepsilon_{D,p}-1} - \tilde{\theta} - \tau} \cdot (1 - \varepsilon_{x,p}) = 0, \tag{14}$$

$$\varepsilon_{x,\theta} \cdot \left(\tilde{\phi} \cdot \varepsilon_{D,x} - \frac{\tilde{\theta}}{\frac{\varepsilon_{D,p}}{\varepsilon_{D,p}-1} - \tilde{\theta} - \tau}\right) = 0, \tag{15}$$

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.

Theorem 3 (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*

$$\tilde{\phi} = \frac{1}{\varepsilon_{D,p} - \varepsilon_{D,x}}, \tag{16}$$

$$1 - \tilde{\theta} = 1 - \left(1 - \tau + \frac{1}{\varepsilon_{D,p} - 1}\right) \cdot \frac{\varepsilon_{D,x}}{\varepsilon_{D,p}}. \tag{17}$$

Proof. This follows from solving equations (16) and (17) for $\tilde{\phi}$ and $\tilde{\theta}$. □

There are two key differences with the platform's optimal solution. First, the object ϕ is similar to the Lerner index μ but incorporates the welfare of riders through the term $\frac{\varepsilon_{D,p}}{\varepsilon_{D,p}-1}$. This reflects the social planner correcting the Spence inefficiency that occurs under the platform's optimal pricing regime (Weyl, 2010). Second, neither of the socially efficient pricing conditions involves drivers' behavioral responses. This is a consequence of the envelope theorem; adjustments in labor supply that stem from price or commission rate changes do not have a first-order effect on welfare local to the optimum. The magnitude of the change in the wage alone is sufficient.

2.4 Pricing in a Ridesharing Market Place

Two formal definitions help to learn more about these markup and commission rate formulae. 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* κ. *This implies that* $\varepsilon_{D,p} - \varepsilon_{D,x}$ *converges to infinity.*

The definition of perfect competition for drivers is straightforward but the definition for riders needs some explanation. Naturally, perfect competition for riders implies that they are infinitely sensitive to changes in the price and waiting times. However, this does not define the ratio of or difference between these elasticities. To resolve this issue, I assume that the platform's markup, as measured by the Lerner index, converges to zero under perfect competition on both sides of the market. This implies that $\varepsilon_{D,p} - \varepsilon_{D,x}$ converges to infinity and $\frac{\varepsilon_{D,x}}{\varepsilon_{D,p}}$ converges to a constant.

The clearest implication of the platform's optimal commission rate (11) is that platforms use monopsony power to raise their commission rate. Relative to a scenario with perfect competition for drivers, the commission rate is $\frac{\varepsilon_{D,x}}{\varepsilon_{D,p}} \cdot \frac{1-\tau}{1+\varepsilon_{H,w}} \cdot 100$ 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

$$\lim_{\varepsilon_{H,w}\to\infty} 1-\theta^* = 1-(1-\tau)\cdot\frac{\varepsilon_{D,x}}{\varepsilon_{D,p}}. \tag{18}$$

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 (18) maximizes the wage rate when there is perfect competition for riders.

The optimal markup condition in equation (10) 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

$$\lim_{\varepsilon_{H,w}\to\infty}\mu^* = \frac{1}{\varepsilon_{D,p}-\varepsilon_{D,x}}. \tag{19}$$

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

$$\varepsilon_{\mu^*,\varepsilon_{H,w}} = -\frac{\varepsilon_{H,w}\cdot(1-\kappa)}{1+\varepsilon_{H,w}\cdot(1-\kappa)}, \tag{20}$$

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. To a first order approximation, this suggests that encouraging more competition for drivers causes a transfer from riders to drivers and leaves the platform unaffected when starting from an extremely monopsonistic position.

2.5 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,[9] 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 different variables costs to mediating exchanges between buyers and sellers. As discussed in more detail later, this feature can reflect taxes and insurance premiums *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 are 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.

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

3 Redesigning the Market

This subsection considers alternative market designs to remedy platform market power and, in particular, monopsony power. Specifically, I consider a strategically set commission cap to raise worker welfare and minimum wages for utilized hours, as has been implemented by many state and local governments in the US (*e.g.*, most recently in Minneapolis, Minnesota).

3.1 Commission Caps and Driver Unionization

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 (17). 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

$$\max_{\theta} p \cdot \theta \cdot x \text{ subject to } p = P(\theta) \text{ and } D(p, x) = x \cdot H(p \cdot \theta \cdot x), \tag{21}$$

which yields the first-order condition

$$1 + \varepsilon_{P,\theta} - \tilde{\varepsilon}_{x,\theta} = 0, \tag{22}$$

where $\varepsilon_{P,\theta} = \frac{\partial P(\bullet)}{\partial \theta} \cdot \frac{\theta}{P(\bullet)}$. The definition of $\tilde{\varepsilon}_{x,\theta}$ remains the same as $\varepsilon_{x,\theta}$ but the expression differs from equation (8) because the union internalizes the best response of the platform in the equilibrium condition. Now, this elasticity equals

$$\tilde{\varepsilon}_{x,\theta} = \frac{\varepsilon_{D,p} \cdot \varepsilon_{P,\theta} + \varepsilon_{H,w} \cdot (1 + \varepsilon_{P,\theta})}{\varepsilon_{D,x} + 1 + \varepsilon_{H,w}}. \tag{23}$$

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

$$\varepsilon_{P,\theta} = \frac{\theta}{1 - \theta - \tau}. \tag{24}$$

Theorem 4 (The union's commission rate.)**.** *The commission rate that maximizes drivers' wages is*

$$1 - \theta^{**} = 1 - (1 - \tau) \cdot \frac{\varepsilon_{D,x}}{\varepsilon_{D,p}} \cdot \frac{1 + \varepsilon_{D,x}}{\varepsilon_{D,x}}. \tag{25}$$

Proof. This follows from plugging equations (23) and (24) into equation (22). □

Comparing this condition to equation (11) reveals that the wage maximizing commission rate is necessarily lower than the level set by a monopsonistic platform. Rather than marking up the commission rate according to the labor supply elasticity, the union marks down the commission rate by the elasticity of demand to utilization. Given that the socially efficient commission rate (17) is also lower than the platform's preference, the wage maximizing commission rate is closer to the socially efficient level provided there is not too much market power over riders. In fact, the social planner and the union's optimal commission rate 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.

Driver wages and welfare. Under the assumption of an isoelastic labor supply function, drivers' surplus in this market equals

$$U(w) = \frac{w \cdot H(w)}{1 + \varepsilon_{H,w}}. \tag{26}$$

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

$$\varepsilon_{U,\theta} = (1 + \varepsilon_{H,w}) \cdot \varepsilon_{w,\theta}, \tag{27}$$

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

$$\varepsilon_{w,\theta} = 1 + (1 - \varepsilon_{x,p}) \cdot \varepsilon_{P,\theta} - \varepsilon_{x,\theta}, \tag{28}$$

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.

3.2 A Minimum Wage on Utilized Hours

This subsection considers setting a minimum wage for workers' utilized hours $\bar{w}$ (*i.e.*, ensuring that $p \cdot \theta$ does not fall below a threshold). Absent this policy, the platform's pricing decisions imply there is an equilibrium total wage rate equal to

$$w^* = p^* \cdot \theta^* \cdot x.$$

To demonstrate the impact of this policy I will set $\bar{w} = p^* \cdot \theta^*$, which leaves the wage rate unchanged, and then evaluate the effect on total wages of marginally decreasing

$\bar{w}$. This is summarized by

$$\varepsilon_{w^*,\bar{w}} = 1 - \varepsilon_{x,\bar{w}}, \tag{29}$$

where $\varepsilon_{x,\bar{w}} = -\frac{dx}{d\bar{w}} \cdot \frac{\bar{w}}{x}$. The elasticity of utilization to the minimum wage $\varepsilon_{x,\bar{w}}$ can be expressed in terms of behavioral elasticities after differentiating the equilibrium condition with the minimum wage substituted in

$$D\left(\frac{\bar{w}}{\theta}, x\right) = x \cdot H(\bar{w} \cdot x), \tag{30}$$

which gives

$$\varepsilon_{x,\bar{w}} = \frac{\varepsilon_{D,p} \cdot (1 - \varepsilon_{\theta,\bar{w}}) + \varepsilon_{H,w}}{1 + \varepsilon_{H,w} + \varepsilon_{D,x}}, \tag{31}$$

where $\varepsilon_{\theta,\bar{w}} = \frac{d\theta}{d\bar{w}} \cdot \frac{\bar{w}}{\theta}$. Equation (31) contains the elasticity of the commission rate to the minimum wage, which captures the platform's pricing response to the minimum wage inside the broader equilibrium adjustments.

Representing the platform's reaction in terms of market participants' behavioral elasticities requires reassessing the platform's choices. Their optimization problem is now

$$\begin{aligned} \max_{b,\theta} \big[p \cdot (1-\theta) - c\big] \cdot D(p,x) \;\text{ subject to }\; D(p,x) =& x \cdot H(p \cdot \theta \cdot x) \\ \text{and }\; \bar{w} =& p \cdot \theta. \end{aligned} \tag{32}$$

Platform optimization implies that

$$p^{\dagger} = \frac{c + \bar{w}}{1 - \tau} \cdot \frac{\varepsilon_{D,p} - \varepsilon_{D,x} \cdot \check{\varepsilon}_{x,\theta}}{\varepsilon_{D,p} - \varepsilon_{D,x} \cdot \check{\varepsilon}_{x,\theta} - 1}, \tag{33}$$

or, equivalently

$$1 - \theta^{\dagger} = 1 - \frac{\bar{w}}{c + \bar{w}} \cdot (1 - \tau) \cdot \frac{\varepsilon_{D,p} - \varepsilon_{D,x} \cdot \check{\varepsilon}_{x,\theta} - 1}{\varepsilon_{D,p} - \varepsilon_{D,x} \cdot \check{\varepsilon}_{x,\theta}}, \tag{34}$$

where

$$\check{\varepsilon}_{x,\theta} = \frac{dx}{d\theta} \cdot \frac{\theta}{x} = \frac{\varepsilon_{D,p}}{1 + \varepsilon_{H,w} + \varepsilon_{D,x}}, \tag{35}$$

which comes from totally differentiating equation (30) with respect to x and θ. The dagger notation denotes the platform's endogenous choices in this new environment. Equation (33) shows the platform marking up their costs, which now depend on the minimum wage, according to a combination of behavioral elasticities.

The platform's choice of commission rate in equation (34) implies that

$$\varepsilon_{\theta,\bar{w}} = \frac{1}{c + \bar{w}}.$$

Therefore, this minimum wage leaves workers *worse off* if

$$\frac{\bar{w}}{c + \bar{w}} > \frac{\varepsilon_{D,x}}{\varepsilon_{D,p}} \cdot \frac{1 + \varepsilon_{D,x}}{\varepsilon_{D,x}}, \tag{36}$$

which follows from setting $\varepsilon_{w^*,\bar{w}} < 0$ and substituting in the results above.

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. 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 14 percent relative to a benchmark where the commission rate is at the socially efficient level. Despite this, a minimum wage on utilized hours would be unlikely to benefit workers.

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, which puts it around the same size as Amazon. In most areas, workers are free to join and leave the platform and, once on the platform, drivers pick where and when to work. A notable exception is New York. Drivers can also work simultaneously for Uber's competitors like Lyft.

Given the available data, the focus of the analysis in this paper is 2017 in the US.

During this time, passenger fares were determined by time and distance, as well as Uber's surge algorithm. Fares were comprised of two components: the price of the ride and a booking fee. Drivers on the platform received the price component of the fare after the Uber fee, which was a fixed commission rate, was deducted. The entirety of the booking fee was received by Uber and earmarked to cover some costs of mediating the ride.

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 often confused by reasonable alternative definitions arising from the existence of the booking fee for passengers alongside the Uber fee for drivers. However, the model provides a clear theoretical definition of the commission rate: the share of the total price paid by riders—inclusive of the booking fee—that drivers do not receive. Therefore, information on the average fare, booking fee, and Uber fee is necessary to construct an estimate of the commission rate.

I take these numbers from academic publications that have access to proprietary microdata, and cross-check their implications with public sources like online Uber driver fora. Recent papers report an Uber fee ranging from 20 to 28 percent (Caldwell and Oehlsen, 2021; Castillo, 2023; Cook et al., 2021). In the estimation, I use an Uber fee of 25 percent for the central scenario, which seems to be Uber's active choice for the commission rate in 2017.[10] In an earlier working paper from 2019, Castillo (2023) reports a booking fee of $2.30 for Houston, Texas. This is on the higher side of reports of the booking fee from drivers during that period of time, so I opt for a lower booking fee of $1.30 to calculate the overall commission rate. Finally, Cook et al. (2021) reports drivers earnings per trip before the Uber fee which, when combined with the book fee, implies an average price per trip of $11.40.

Overall, these numbers constitute a commission rate of two-thirds, which I use as the central scenario in the analysis below. I also consider commission rates of 39 percent and 29 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

[10] Some drivers had a lower Uber fee in that year because they were grandfathered in from previous regimes.

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". Again for Texas, Houston, Castillo (2023) reports the first two components as comprising three percent of the fare. Insurance costs are paid by the mile at an approximate premium of \$0.30. Combined with the average trip distance, inclusive of distance to pickup, this suggests that insurance costs make up 15 percent of the passenger fare. In total, costs comprise 18 percent of the typical fare which suggests a Lerner index of 0.51. To examine the sensitivity of estimates to uncertainty in this calculation, I also consider total costs equivalent to 13 percent and 23 percent of the fare. For simplicity, I assume these stem from changes in insurance costs.

The third and final empirical moment is the equilibrium response of utilization to a change in price.[11] Hall et al. (2023) report static and dynamic estimates of this statistic, 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 $\hat{\varepsilon}_{H,w}$ (= 6.39) and the following Taylor series approximation

$$\varepsilon_{x,p} \approx \hat{\varepsilon}_{x,p} + \frac{\partial \varepsilon_{x,p}}{\partial \varepsilon_{H,w}} \cdot (\varepsilon_{H,w} - \hat{\varepsilon}_{H,w}) = \hat{\hat{\varepsilon}}_{x,p}, \tag{37}$$
$$\text{where} \quad \frac{\partial \varepsilon_{x,p}}{\partial \varepsilon_{H,w}} = \frac{1 - (\varepsilon_{D,p} - \varepsilon_{D,x})}{(\varepsilon_{D,x} + 1 + \varepsilon_{H,w})^2}.$$

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

Combining the numbers mentioned above with further data on the average num-

[11] 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.

ber of trips per week, hours per week, and driving speed from Cook et al. (2021) implies other interesting numbers. In particular, they suggest an average wage of $14.71, a utilization rate of 51 percent,[12] and a utilized wage rate of $28.96. This is on the high side of Uber's reports of earnings per utilized hour, which suggests that the statistics above do *not* offer a particularly negative picture of drivers' earnings.

4.3 Estimation

I use a generalized method of moments estimator to estimate 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 from equations (8), (10), and (11) using the norm $m(\hat{X}, \boldsymbol{\varepsilon})^T \cdot W \cdot m(\hat{X}, \boldsymbol{\varepsilon})$, where

$$m(\hat{X}, \boldsymbol{\varepsilon}) = \begin{pmatrix} \hat{\mu} - \frac{1+\varepsilon_{D,x}+\varepsilon_{H,w}}{\varepsilon_{D,p}+\varepsilon_{H,w}\cdot(\varepsilon_{D,p}-\varepsilon_{D,x})} \\ \\ \widehat{(1-\theta)} - 1 - (1-\tau) \cdot \frac{\varepsilon_{D,x}}{\varepsilon_{D,p}} \cdot \frac{\varepsilon_{H,w}}{1+\varepsilon_{H,w}} \\ \\ \hat{\hat{\varepsilon}}_{x,p} - \frac{\varepsilon_{D,p}+\varepsilon_{H,w}}{\varepsilon_{D,x}+1+\varepsilon_{H,w}} \end{pmatrix}, \tag{38}$$

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 quantitative models have not been able to reconcile Uber's behavior with profit maximization. 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

[12]This utilization rate only includes time with passengers and corresponds to x in the model.

	Data moment	Model prediction
Commission rate	0.34	0.34
Markup ratio	0.51	0.51
Utilization elasticity	1.4 [0.65, 2.15]	1.18

Table 1: Model Fit

Notes: This table shows the targeted moments in the first column, their empirical estimates in the second column, and the model's predictions of these moments in the third column. The numbers in the parentheses are the 95 percent confidence interval for the empirical estimate of the utilization elasticity.

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 less relevant to Uber's long-term pricing decisions, which should account for more flexible behavioral responses and the potential of new entrants. Indeed, other long-term pricing experiments on the Uber platform have found much larger elasticities (Christensen and Osman, 2023).

4.4 Seattle's *Fare Share* Ordinance

Another way to evaluate the model is to test its out-of-sample performance. In this subsection, I compare the fallout of Seattle's *Fare Share* ordinance, which came into force at the start of 2021, with the model's predictions. This regulation effectively placed a minimum wage on workers' utilized hours by imposing minimum levels of payments to drivers based on a trip's distance and duration.[13] In response, Uber raised prices by 40 percent.[14]

Interpreting this through the lens of equation (33), which describes a platform's optimal pricing in the presence of minimum wages for utilized hours, Uber's response implies the regulation raised utilized wages by 48 percent on average. This follows from the fact that $\varepsilon_{p,\bar{w}} = 0.83$ when evaluated at the calibrated level of costs and utilized wage rate. A 48 percent increase in utilized wages is consistent with the increase in labor costs that Uber reports for similar policies; the platform estimates that its

[13] At the time, drivers were required to receive at least \$1.33 per mile and \$0.57 per minute, or a minimum of \$5.00 per trip. This has since been superseded by state-level legislation that requires at least \$1.55 per mile and \$0.66 per minute, or \$5.81 per trip

[14] See this Uber blog post.

labor costs will rise by up to 40 percent in the face of new proposals in Minnesota,[15] which are less tough than those for Seattle at the time.

Then, to satisfy the minimum wage on utilized hours, the platform would have to raise commission rates by three percentage points. This small increase in commission rates is consistent with the model, which predicts that Uber would respond to the policy primarily through price adjustments rather than changes in commission. Consequently, utilization would fall by 56 percent and overall wages would fall by eight percent. Uber reports that wages per online hour fell by ten percent,[16] matching the model's prediction closely.

The takeaways from this subsection are twofold. First, the model accurately predicts the response of prices and equilibrium outcomes to policy interventions out-of-sample. Second, minimum wages on utilized hours are a flawed policy to raise worker welfare in the face of platform monopsony power.

4.5 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 ratio of the elasticity of demand to utilization and price $\frac{\varepsilon_{D,x}}{\varepsilon_{D,p}}$. When multiplied by $(1-\tau)$, this equals one minus the commission rate under a perfectly competitive driver market. The fact that all these ratios with this adjustment equal one minus the cost share 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 4.27. 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 2.36. The highest estimate of the driver supply elasticity is 11.63, however, this requires both the highest costs and lowest commission rate.

In a standard model of wage-posting by a monopsonistic employer, the driver sup-

[15] See this Uber blog post

[16] Again, see this Uber blog post.

		Commission rate		
		39%	34%	29%
	13%	$\frac{\varepsilon_{D,x}}{\varepsilon_{D,p}} = 0.90$ (<0.01)	$\frac{\varepsilon_{D,x}}{\varepsilon_{D,p}} = 0.90$ (<0.01)	$\frac{\varepsilon_{D,x}}{\varepsilon_{D,p}} = 0.90$ (<0.01)
		$\varepsilon_{H,w} = 2.36$ (<0.01)	$\varepsilon_{H,w} = 3.23$ (0.01)	$\varepsilon_{H,w} = 4.39$ (0.01)
Costs	18%	$\frac{\varepsilon_{D,x}}{\varepsilon_{D,p}} = 0.84$ (<0.01)	$\boldsymbol{\frac{\varepsilon_{D,x}}{\varepsilon_{D,p}} = 0.84}$ **(<0.01)**	$\frac{\varepsilon_{D,x}}{\varepsilon_{D,p}} = 0.84$ (<0.01)
		$\varepsilon_{H,w} = 2.92$ (0.01)	$\boldsymbol{\varepsilon_{H,w} = 4.27}$ **(0.02)**	$\varepsilon_{H,w} = 6.37$ (0.03)
	23%	$\frac{\varepsilon_{D,x}}{\varepsilon_{D,p}} = 0.79$ (<0.01)	$\frac{\varepsilon_{D,x}}{\varepsilon_{D,p}} = 0.79$ (<0.01)	$\frac{\varepsilon_{D,x}}{\varepsilon_{D,p}} = 0.79$ (<0.01)
		$\varepsilon_{H,w} = 3.84$ (0.02)	$\varepsilon_{H,w} = 6.31$ (0.03)	$\varepsilon_{H,w} = 11.63$ (0.08)

Table 2: Parameter Estimates

Notes: This table shows a matrix of parameter estimates for nine different combinations of Uber's commission rate and costs. Left to right shows increasingly lower commission rates. Up to down shows increasingly higher costs. Parentheses show corresponding standard errors. The estimates in the central cell in bold are the central scenario.

ply elasticities map directly to a wage markdown of $1/(1+\varepsilon_{H,w})$. For the central estimate, this implies that workers would be denied one-fifth of their marginal product. In the two-sided market described in section 2, this is not the case because equilibrium adjustments in utilization determine wages.

4.6 Counterfactuals

This subsection considers two counterfactuals to quantitatively understand how monopsony power affects wages and, in turn, worker welfare in a two-sided ridesharing market: a commission cap set to maximize driver welfare and a minimum wage that applies for workers' utilized hours.

4.6.1 Commission Caps

Motivated by the theoretical result that the wage maximizing commission rate equals the first-best under perfect competition for riders, which applies to the case of Uber, I consider setting θ equal to $(1-\tau)\cdot\frac{\varepsilon_{D,x}}{\varepsilon_{D,p}}$, leaving the behavioral elasticities constant, and allowing the platform to respond with rider prices. Therefore, this could constitute a counterfactual where we let drivers collectively set the commission rate. An ad-

		Commission rate		
		39%	34%	29%
	13%	$\%\Delta w = 34$ $\%\Delta U = 114$	$\%\Delta w = 23$ $\%\Delta U = 98$	$\%\Delta w = 16$ $\%\Delta U = 84$
Costs	18%	$\%\Delta w = 23$ $\%\Delta U = 92$	$\%\boldsymbol{\Delta}\mathbf{w} = \mathbf{14}$ $\%\boldsymbol{\Delta}\mathbf{U} = \mathbf{74}$	$\%\Delta w = 8$ $\%\Delta U = 58$
	23%	$\%\Delta w = 14$ $\%\Delta U = 70$	$\%\Delta w = 7$ $\%\Delta U = 50$	$\%\Delta w = 2$ $\%\Delta U = 31$

Table 3: Welfare Effects of a Commission Cap

Notes: This table shows a matrix of estimates for changes in Uber's wage $\%\Delta w$ and worker surplus $\%\Delta U$ estimates for nine different combinations of Uber's commission rate and costs. Left to right shows increasingly lower commission rates. Up to down shows increasingly higher costs. The estimates in the central cell in bold are the central scenario.

ditional advantage of this formulation is that it leaves the denominator in the welfare expression (26) constant, and the platform's pricing adjustment is straightforward.

Using equations (27) and (28), table 3 presents estimates of the impact of monopsony power on wages w and the worker surplus from Uber's marketplace U in terms of percentage changes. The central estimate in bold implies that drivers' wages would rise by 14 percent in equilibrium. It is possible to decompose this change in wages using equation (28) as follows

$$\%\Delta w = \left[1 + \underbrace{(1 - \varepsilon_{x,p}) \cdot \varepsilon_{P,\theta}}_{\text{(1-1.18)}\times\text{2.17=-0.39}} - \underbrace{\varepsilon_{x,\theta}}_{\sim 0}\right] \cdot \underbrace{\%\Delta\theta}_{0.23} \approx 14. \tag{39}$$

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 2.17, as computed from equation (24). 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-third below their counterfactual equivalent. At the lower end, wages are only minimally affected by a small amount of monopsony power but this scenario requires a low level of commission, which Uber no longer offers, and a high level of costs. Taken together, the evidence suggests that the platform materially depresses wages relative to the counterfactual. However, these estimates are 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), and they incorporate the attenuating effect of fare and utilization adjustments.

Table 3 also reports the overall effect on the ridesharing worker surplus of these wage changes, which rely on the assumption of an isoelastic driver supply function. This counterfactual leads to large welfare gains for workers. A 14 percent increase in wages raises the worker surplus from Uber's marketplace by close to three-quarters. Translating these welfare effects in the ridesharing market to overall welfare requires multiplying by the share of income that workers derive from ridesharing under the assumption that the labor supply elasticity to other markets is the same as to ridesharing, which seems reasonable given similar estimates for other labor markets (Lamadon et al., 2022). In this case, somewhere on the order of one-quarter of gig economy participants' income is earned through ridesharing, which suggests that the counterfactual could raise overall welfare for Uber's 1.5 million US drivers by almost one-fifth.

4.6.2 Minimum Wages

In terms of a minimum wage on utilized hours, estimates of the model's parameters and the prevailing average wage level suggest that this policy is unlikely to help workers. Evaluating the left-hand side of inequality (36) at the *status quo* utilized wage and costs level equals 0.82, which is very close to the right-hand side of 0.85. This indicates there is little room for minimum wages on utilized hours to raise worker welfare in the gig economy, as exemplified by the discussion of Seattle's *Fare Share* ordinance in section 4.4.

Interestingly, the minimum wage is ineffective despite the existence of significant monopsony power. Intuitively, the minimum wage allows the platform to select its optimal mix of the price and commission rate while satisfying the minimum wage. This additional flexibility relative to a commission cap leaves the platform capable of exploiting their sources of market power and the policy fails to target the welfare relevant quantity, which is equilibiurm wages.

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 15 percentage points, wages would increase by 14 percent, and worker welfare would increase dramatically.

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