Monopsony Power in the Gig Economy

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Abstract

Many workers provide services for customers via digital platforms that may exert monopsony power. Typical expositions of labor market power are inapplicable in this context because platforms post prices to both sides of a two-sided market instead of setting wages. Further, platform-specific labor supply is hard to measure when workers multi-app. This paper develops a model of a gig labor market that resolves these issues. Platforms exploit monopsony power to markup their commission rate, reduce equilibrium wages, and do not lower prices for customers. Estimating the model with public data on Uber implies that the platform uses labor market power to depress drivers' earnings by 15 percent. Commission caps are an effective policy to raise worker welfare, while minimum wages on utilized hours, which are common, likely harm workers.

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1 Introduction

Digital platforms, like Amazon's marketplace and Uber's ridesharing platform, often operate two-sided markets that facilitate exchanges between buyers and sellers (Rysman, 2009). In this setting, concerns over market power may arise because strong network effects mean participants benefit from being in the same marketplace, and individuals are atomistic relative to platforms. However, the very existence of network externalities can make platforms reluctant to exploit market power over one side of the market if it harms the other side. Consequently, it is unclear when these worries are warranted (Jullien et al., 2021).

This issue is prescient for labor economists studying monopsony power given the rise of gig work, where hundreds of millions of workers around the world provide short-term and independent labor services via digital intermediaries (Datta et al., 2023; Dube et al., 2020).[1] Concerns around monopsony power in the gig economy are particularly pronounced given workers' self-employed status, which offers few protections, and fears over poor outside options owing to, for example, underemployment (Lachowska et al., 2023). Yet, policymakers lack a framework of how monopsony power manifests in the gig economy, where platforms post prices and commission rates rather than wages, and what remedies may be effective.

This paper develops a tractable model to study a typical gig labor market: ridesharing. Alongside food delivery, this industry represents 90 percent of the over five million platform workers in the US (Garin et al., 2023). The model provides clear insights into platform pricing, the merits of different policy interventions, and their interplay with market power from both a platform and a social planner's perspective. Estimating the model requires only a small number of statistics and circumvents the need to measure drivers' platform-specific hours, which is difficult when workers multi-app and are not obliged to accept rides (Hyman et al., 2020).[2]

I demonstrate the framework's utility by testing its out-of-sample predictions and evaluating the extent of market power enjoyed by the US's largest ridesharing platform, Uber.[3] Public data, including causal estimates from the platform's pricing experiments, indicate substantial monopsony power over drivers and a competitive

[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 this context, 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. In what follows, this is only an issue of semantics.

[2] This measurement issue has prevented the implementation of a minimum wage for gig workers (Harris and Krueger, 2015).

[3] Bloomberg estimates the platform accounts for 75 percent of the US ridesharing industry.

market for passengers. The analysis suggests Uber finds it profitable to charge drivers a high commission rate, which reduces their labor supply and increases waiting times. Passengers are not compensated for the latter with lower prices because this would increase congestion further. Consequently, monopsony power hurts both drivers and passengers—a key legal test in the US for anti-trust in two-sided markets.[4]

Quantitatively, the commission rate is 15 percentage points higher than the social planner's optimum. If this were restored to its first-best level, wages would increase by 14 percent after accounting for the platform's pricing response. This captures almost all of the increase in wages that would occur under perfect competition. In contrast, the model reveals that minimum wages on utilized hours, which set a lower bound on a combination of commission rates and prices, harm workers because platforms increase prices, dampening demand and, in turn, equilibrium wages.

This has practical policy implications. State and local governments already enact minimum wages on utilized hours, which jointly constrain commission rates and prices,[5] so commission caps alone are feasible, simpler, and more effective. The model highlights two additional benefits of commission caps as a response to monopsony power. First, given the power to set commission rates, policymakers can induce variation sufficient to identify the optimal policy. Second, drivers collectively would set the first-best commission rate if they had the choice, so this policy could be reliably informed by intelligence from marketplace participants.

Concretely, the model considers a ridesharing platform 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 determines waiting times under various micro-foundations. Hourly wages, which also depend on utilization since drivers are only paid when they carry passengers, determine the supply of drivers. The market reaches equilibrium through adjustments in worker utilization; drivers enter and exit as their wage rate moves with utilization, and riders change their demand as waiting times fluctuate accordingly (Hall et al., 2023).[6] This implies a fixed point equilibrium condition that constrains the platform's problem.

[4] See 16-1454 Ohio v. American Express Co. (06/25/2018).

[5] This is done by ensuring minimum payments to drivers for time spent with passengers in their vehicle.

[6] The model has implications outside of ridesharing for two reasons. First, the role of utilization is an alternative specification of network effects that is relevant to other markets that exhibit congestion, like food delivery. The framework can inform other markets, too. For example, differentiated consumer goods with centrally set prices. In this case, the higher the price, the more products are supplied, and the more likely a consumer will find something close to their ideal variety. I thank Catherine Thomas for this clarifying comment. Second, in terms of empirical content, the strength of monopsony power is likely to be similar across different gig labor markets within the same geography if market power comes from a common source, such as unattractive alternatives outside of the gig economy.

The model delivers clear intuitions about decision-making by digital intermediaries and how they contrast with a social planner. Three behavioral elasticities describe how platforms incorporate market power into their optimal choice of price and commission rate. First, the elasticity of driver supply to hourly earnings corresponds to the extent of monopsony power. Second, the elasticity of passenger demand to price, and third, the elasticity of passenger demand to utilization (or waiting times). The latter two elasticities jointly reflect a platform's monopoly power, but their relative magnitudes are important for pricing.

Platforms markup the commission rate that drivers pay when they enjoy monopsony power. Equivalently, the platform reduces drivers' keep rate identically to markdowns in textbook wage-posting models (Manning, 2011). To this extent, the platform-specific labor supply elasticity is still a useful measure of monopsony power in this context, but it is an incomplete picture. Demand elasticities for price and waiting times, and a precise counterfactual, which dictates the response of passenger prices and driver utilization, are necessary to infer the equilibrium impact on wages.

The relative magnitude of price and waiting time elasticities also determines commission rates; if waiting times are important to customers, the platform reduces its commission to encourage driver supply. Conversely, the driver supply elasticity does not affect passenger prices, so the platform does not pass on the benefits of monopsony power to riders. The platform increases its commission rate instead of passing on savings to customers because price reductions trigger longer waiting times and dampen demand, which makes this strategy unattractive. Therefore, both sides of the market are left worse off by the presence of labor market power.

The small number of parameters in the model makes it easy to estimate with little information, which is especially valuable in a context where data is proprietary and collaborations on contentious topics are not feasible. Further, by virtue of inferring the model's parameters from platform choices, any empirical analysis is readily reconcilable with profit maximization. This has not been possible in other studies of multi-sided transport markets that provide a more detailed description of participants' interactions but yield behavioral responses inconsistent with standard firm objectives (Castillo, 2023; Rosaia, 2020; Sullivan, 2022).

To illustrate the model's practicality, I evaluate the extent of Uber's market power over the US ridesharing industry—an important issue in its own right. In the US, there are 1.5 million drivers actively working on the platform and over six million globally. Moreover, despite evidence that many workers benefit substantially from the opportunity to partake in ridesharing 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). Therefore, quantifying monopsony power over workers in ridesharing markets and potential remedies is a first-order policy question.

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".[7] 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 identify the behavioral elasticities that Uber faces, I use public information on the platform's choice of commission rate and passenger prices around 2017, as well as data on costs and results from a randomized pricing experiment. These numbers imply, for example, a commission rate of over one-third and mediation costs equivalent to 18 percent of the fare (Castillo, 2023; Cook et al., 2021). Over a six-month horizon, Hall et al. (2023) estimate an elasticity of utilization to price above one, which reflects a causal response comprised of behavioral responses. The model matches the data closely and accurately predicts out-of-sample the impact of a policy in Seattle, validating the structural assumptions that support counterfactual analysis.

Bringing the model to the data suggests that Uber exerts substantial monopsony power over drivers and faces strong competition for riders. The central scenario implies the platform faces a labor supply elasticity of 4.27.[8] Viewed through the model, this suggests the commission rate is 15 percentage points above the competitive benchmark, which corresponds to a wage markdown of one-fifth in standard wage-posting models. However, in gig labor markets, prices and utilization are endogenous and also determine wages. Therefore, it is necessary to consider a precise counterfactual to understand the impact of monopsony power on wages and worker welfare.

I consider introducing a commission cap set at the first-best level as a potential remedy to monopsony power noting its legal precedent and practical feasibility. In this scenario, a commission rate fall of 15 percentage points triggers the platform to raise prices by almost half. In turn, utilization falls by two-thirds so that, overall, wages rise by 14 percent, and welfare increases by roughly 20 percent. The efficacy

[7] See Dara's interview with The Rideshare Guy here. The "take rate" is another phrase for commission.

[8] This number is close to estimates found across US labor markets in Lamadon et al. (2022), despite the different estimation approach.

of this policy stands in contrast to the impact of minimum wages for utilized hours, which are prevalent in the US. The model shows that these policies lead platforms to increase prices much more than commission rates. This causes a fall in utilization and, overall, driver wages decrease—opposite to the intention of the policy.

Related literature. This paper contributes to three literatures. First, there is a large and growing body of work evincing the existence of employer monopsony power in different labor markets (see Azar and Marinescu (2024); Caldwell et al. (2024) and Manning (2021) for a review of empirical work, and Kline (2025) for an overview of theoretical treatments). This paper contributes a tractable framework to expand this analysis to multi-sided labor markets and, to my knowledge, provides the first theoretically grounded estimates of monopsony power in the gig economy. Notably, the two-sided nature of this study connects it with recent work evaluating the interaction of product and labor market power (Kroft et al., 2020; Van Reenen, 2024).

Second, this paper adds to the extensive literature on minimum wages in traditional labor markets (Dube (2019); Berger et al. (2025); Horton (2025); Neumark and Shirley (2022); Vergara (2023), to name some recent work), which closely relates to a broader body of work on pricing regulations (*e.g.*, in the rental market (Diamond et al., 2019; Glaeser and Luttmer, 2003) and in credit card markets (Rysman, 2007)). This paper derives conditions under which commission caps and minimum wages on utilized hours can improve worker welfare in the gig economy. Again, to my knowledge, these conditions provide the first formalization of intuitions motivating empirical analyses of commission caps (*e.g.*, in Sullivan (2022) and Li and Wang (2024)) and active policy interventions in several US cities and states.

Third, this paper builds on empirical and theoretical research in two-sided markets more broadly (Jullien et al., 2021; Rochet and Tirole, 2003; Rysman, 2009). Empirically, it estimates a model of a two-sided market that is reconcilable with platform profit maximization and, thus, amenable to considering counterfactual pricing responses. This contrasts with richer models of multi-sided markets that keep prices fixed in counterfactuals or introduce non-structural parameters into platforms' objective functions (Lee, 2013; Yu, 2024). Theoretically, this paper contributes a tractable model of a two-sided marketplace with congestion and multi-homing (Belleflamme and Toulemonde, 2009; Karle et al., 2020). The model's parsimony yields novel insights into asymmetric seesaw effects and may prove useful for pedagogical purposes.

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, section 5 assesses the impact of Uber's market power on workers' wages and welfare, and section 6 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.

2.1 Market Participants, Wages, and Equilibrium

This subsection describes 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 workers' *platform-specific* labor supply.

Riders. Passengers demand hours of transportation which is described in aggregate via a demand function $D(p, x)$. Their demand depends on the price of an hour of ridesharing services p and driver utilization x, which determines waiting times. This assumption has two alternative micro-foundations. First, 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).[9] Second, 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.

Wages. Hourly wages are an equilibrium quantity. They 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

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

Equilibrium. The marketplace equilibrates through adjustments in utilization after the platform has set its prices; drivers enter and exit as their wage rate moves with utilization while riders also change their demand as waiting times fluctuate. 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 such that 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 $\frac{\partial H(w)}{\partial w} > 0$, $H(w) \geq 0$, $\frac{\partial D(p,x)}{\partial x} < 0$, 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

[9] The assumption abstracts from scale effects, which refers to the idea that if the number of drivers and passengers in a market doubled, then waiting times would fall (Arnott, 1996; Castillo and Mathur, 2023). I do not have sufficient data to directly test this mechanism, but I examine the estimated model's out-of-sample predictions in subsection 4.4. The model accurately predicts equilibrium responses to an observed policy change, which suggests that scale effects are not strong enough to influence outcomes in policy-relevant counterfactuals. That is, plausible policy interventions are either not sufficiently large to cause meaningful changes in marketplace scale, or scale effects are not very big.

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.*, taxes and transaction fees) and c denotes other costs of mediation (*e.g.*, insurance premiums). Platform optimization yields two first-order conditions (4) and (5) 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 $\mu = \frac{p\cdot(1-\theta-\tau)-c}{p\cdot(1-\theta-\tau)}$.[10] The latter term is a Lerner-type index (Lerner, 1934), which equals the share of platform revenue that is profited from one hour of ridesharing after the platform pays drivers, 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. First, higher prices reduce demand in the traditional sense. Second, 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. Intuitively, the numerator of equations (6) and (7) reflect the direct effect of their respective price and commission rate changes, while the denominators capture equilibrium effects.

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

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

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

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

when $\varepsilon_{H,w} > 0$, $\varepsilon_{D,x} > 0$, *and* $\varepsilon_{D,p} > 1+\varepsilon_{D,x}$.

Proof. Substituting equations (6) and (7) into the first-order conditions (4) and (5), and rearranging gives expressions (8) and (9). □

Below, I treat $\varepsilon_{D,p}$, $\varepsilon_{D,x}$, and $\varepsilon_{H,w}$ as structural parameters that are invariant to counterfactual scenarios, which I discuss in subsection 2.5. Given this, two formal definitions are helpful to better understand the implications of Theorem 1 and other results below.

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; the platform has no monopsony power when drivers are infinitely sensitive to changes in their wage. For riders, perfect competition implies that they are infinitely sensitive to changes in the price and waiting times. But this does not define the ratio of or difference between these elasticities. To resolve this, I assume that the platform's Lerner index converges to zero under perfect competition on both sides of the market, which requires $\varepsilon_{D,p}-\varepsilon_{D,x}$ and $\frac{\varepsilon_{D,x}}{\varepsilon_{D,p}}$ converge to infinity and a constant, respectively.

2.3 Discussion

This subsection discusses results relating to the platform's optimal pricing formulae and other aspects of the model.

Prices. The platform determines the price for passengers by marking up marginal costs according to the rider-side behavioral elasticities. Two factors affect the markup. First, if riders are elastic to waiting times relative to price, which is captured by the

$\frac{\varepsilon_{D,x}}{\varepsilon_{D,p}}$ term in equation (8), then the platform sets a higher price. This is socially efficient; the platform is internalizing the congestion effects of lower prices on the network. Second, if the platform has some monopoly power then it sets higher prices, and this is socially inefficient.

Pricing equation (8) is noticeable for not including the platform-specific labor supply elasticity. This implies that the platform does not use monopsony power to benefit passengers in terms of lower prices. In other words, there is no "seesaw" effect for rider prices (Rochet and Tirole, 2003, 2006). The platform prefers to increase its commission rate instead of passing on savings to customers because price reductions trigger longer waiting times and dampen demand, which makes this strategy unattractive. In other words, conditional on an optimal commission rate, the price is set to maximize the total revenue extracted from riders. This has important anti-trust implications because abusing labor market power damages both sides of the market, which is the relevant legal test set by the US Supreme Court in Ohio v. American Express Co., 585 U. S. 529, (2018) for two-sided markets.

Commission rates. The clearest implication of equation (9) is that platforms use monopsony power to raise their commission rate through the term $\frac{\varepsilon_{H,w}}{1+\varepsilon_{H,w}}$. All else equal, this is equivalent to reducing workers' wages by $\frac{1}{1+\varepsilon_{H,w}}$ percent—the same markdown as in one-sided labor market models of monopsony power with wage-posting (Manning, 2011). However, in two-sided markets, 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 these mechanisms in section 3.

Interestingly, commission rates will not necessarily only recoup marginal costs absent monopsony power. In particular, the commission rate under perfect competition for drivers equals

$$\lim_{\varepsilon_{H,w}\to\infty} 1-\theta^* = 1-(1-\tau)\cdot\frac{\varepsilon_{D,x}}{\varepsilon_{D,p}}. \tag{10}$$

In this instance, the ratio of demand elasticities also determines the commission rate. 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 (10) maximizes the wage rate when there is perfect competition for riders.

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

$$\lim_{\varepsilon_{H,w}\to\infty} \mu^* = \frac{1}{\varepsilon_{D,p} - \varepsilon_{D,x}}. \tag{11}$$

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.

2.4 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, under an iso-elastic assumption, the social planner faces the following problem

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

That is the social planner places equal weight on the platform's profits, rider surplus, and consumer surplus. The social planner's objective function can be rewritten as an alternative parameterization of the platform's problem after incorporating the equilibrium constraint as follows

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

which leads to the following result.

Theorem 2 (Efficient competitive private equilibrium)**.** *The private equilibrium, which is described by equations (8) and (9), is socially efficient if both sides of the market are perfectly competitive.*

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. $\square$

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 result contrasts with work that shows platform competition can be harmful (Frechette et al., 2019; Hagiu and Jullien, 2014; Tan and Zhou, 2021). The key distinction in this model is that the ratio of agents on either side of the market governs network effects, rather than the number of participants on the other side of the market. Therefore, in markets where the former is a better description, greater competition brings private equilibrium outcomes closer to the socially efficient level. More generally, platform competition may be attractive when it increases behavioral elasticities but does not affect marketplace scale, which is more likely when market participants can multi-app and where competition comes from the threat of entry by new platforms, or from customer adoption of outside options.[11]

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 price and commission rate can be expressed as a function of elasticities that describe driver and passenger behavior*

[11] In practice, the coincidence of the platform's and the social planner's objective function under perfect competition is convenient in that it allows for a sole focus on distortions arising from market power. Further, the empirical counterfactuals below do not change the degree of competition but rather consider alternative market designs, such as commission caps and minimum wages.

as follows

$$\tilde{p} = \frac{1}{1 - (\frac{1}{\varepsilon_{D,p}} + \frac{\varepsilon_{D,x}}{\varepsilon_{D,p}})} \cdot \frac{c}{1-\tau} \cdot \frac{\varepsilon_{D,p} - 1}{\varepsilon_{D,p} + \frac{\tau}{1-\tau}}, \tag{16}$$

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

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 social planner reduces passenger prices relative to the private equilibrium by multiplying p^* with the third term in equation (16). The correction does not include $\varepsilon_{D,x}$ because the platform incorporates the social planner's concern that new passengers hurt others through longer waiting times. However, the social planner must correct the monopolistic distortion. Note, that because behavioral elasticities are held constant, there is no Spence inefficiency that occurs under the platform's pricing regime.[12]

Second, neither of the socially efficient pricing conditions involves drivers' behavioral responses. This is a consequence of the envelope theorem. Changing either the price or commission rate affects drivers by putting more or less money in their pockets, keeping behavior fixed, and by causing a labor supply response. The latter has no effect on social surplus because payments in this market are simply a transfer between the platform, passengers, and drivers. Further, the downstream behavioral responses do not have a first-order effect on driver welfare local to the optimum because of the envelope theorem.

2.5 Discussion

This subsection discusses several aspects of the model outlined above.

Labor supply. The labor supply function $H(w)$ describes the aggregate number of hours drivers work specifically for the platform in question. In practice, measuring labor supply to a particular platform is difficult because platforms only observe when workers are "online", which measures the hours drivers are logged onto the associated application (Hyman et al., 2020). However, online status is costless to maintain because it does not obligate individuals to do anything. For example, drivers can be at home without the intention of accepting jobs but still appear online, or they may

[12]With heterogeneous demand elasticities, a monopolistic platform would lead to a Spence inefficiency because the platform internalizes network effects for the marginal but not the average rider (Weyl, 2010).

be working for a competing platform. Therefore, even in proprietary data, measures of labor supply do not necessarily map to $H(w)$.

This paper exploits the observation that platforms do not need to observe $H(w)$ to optimize; instead, they can experiment to discover profit-maximizing prices. Therefore, it is possible to infer features of the structure of platform-specific labor supply by mapping platform choices to, for example, elasticities using insights from the model. Section 4.3 exploits this intuition to bring the model to the data. The fact that many gig platforms, including Uber, openly experiment with pricing supports the use of this logic in practice.

Pricing. The model assumes that the platform enforces a constant price and commission rate. However, platform prices and commission rates may be state-dependent. Rather than accounting for the intricacies of these high-frequency pricing strategies,[13] this model aims to provide a bird's-eye view of platform behavior that is informative of 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,[14] suggests that this is a reasonable description of platform behavior.

Costs. Platforms may face fixed costs in addition to variable costs, such as maintaining the code base and data centers that underlie their services. These costs should not influence optimal pricing, which trades off marginal revenue and costs. However, if fixed costs comprise the bulk of a platform's overall costs, it may implement a reservation profit share for mediating exchanges. This can be incorporated into the model by considering marginal costs that are higher than otherwise. Further, the existence of fixed costs can mean that a platform may not be profitable, but its behavior is still consistent with the model above.

Costs may also stem from attracting and maintaining riders and drivers on the platform. This would be analogous to hiring costs in models of imperfect labor market competition (Manning, 2006). I argue that given the digital nature of most platforms under consideration, such costs are likely subsumed into a platform's fixed

[13] See Castillo (2023) for a treatment of this phenomenon.

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

cost. For instance, the same software facilitates all drivers' on-boarding procedures and riders' details are stored on the same server with low marginal costs.[15]

Profit maximization. Following the literature, the model considers a platform facing a static problem (Jullien et al., 2021). Given the lack of dynamics, it is important to interpret behavioral elasticities as reflecting long-run responses from marketplace participants, which has practical implications in terms of estimation. In particular, it means that elasticities must be informed by responses over a significant time horizon rather than adjustments due to short-run fluctuations. This issue of long-run elasticities connects with the assumption of a profit-maximizing platform.

Existing empirical studies of ridesharing markets generally estimate elasticities to reflect responses to surge pricing (Castillo, 2023; Rosaia, 2020). However, these short-term elasticities are not the behavioral responses that guide baseline platform pricing. Consequently, the implicit elasticities cannot rationalize platform decision-making and non-structural assumptions are necessary to conduct counterfactual analysis.[16] By virtue of estimating parameters from platform choices, which are informed by long-run elasticities, empirical implementations of this model are immediately reconcilable with profit maximization and suitable for counterfactual policy analysis.

Constant behavioral elasticities. In the social planner's problem and for the counterfactual analysis below, I assume that participants' behavioral elasticities are constant. The approach allows for a general interpretation of the results as reflecting changes in equilibrium outcomes under the approximation that these elasticities remain constant. This interpretation is bolstered by the model's strong out-of-sample performance in subsection 4.4, which implies that plausible levels of policy variation are not large enough to significantly affect participants' behavioral responses. However, one caveat is warranted. Participants' elasticities will partially reflect strategic interactions with competing platforms. This makes mapping to welfare quantities via elasticities imperfect (Berger et al., 2022), although it does not affect predictions about wages.[17]

[15] Some empirical evidence of this is the fact that Uber's marketing spend and headcount are only weakly correlated with revenue growth.

[16] These papers assume that platforms maximize a convex combination of profits and participants' welfare, and select the weights on the latter to ensure platform optimization.

[17] One benefit of abstracting from strategic interactions is that it makes the results in this paper comparable with the majority of the literature studying labor market monopsony power, which takes the same approach (Kline, 2025).

3 Redesigning the Marketplace

This section considers alternative market designs to remedy platform monopsony power. Specifically, I consider two policies. First, a commission cap as has been under consideration by policymakers. Second, a minimum wage for utilized hours as has been implemented by many state and local governments in the US (*e.g.*, most recently in Minneapolis, Minnesota). Lastly, I conclude the section by discussing the relevance of these results and other considerations for policymakers.

3.1 Commission Caps

This subsection studies the introduction of a commission cap into a ridesharing marketplace. Proponents of this policy argue that it offers a way to raise worker welfare. Therefore, I begin by evaluating the optimal commission cap from the drivers' perspective before describing its impact on wages and welfare.

The game. To determine drivers' preferred commission cap, I consider a three-period game. In *period one*, an "organization" sets the commission rate to maximize drivers' hourly earnings, as described in equation (1). This is equivalent to maximizing worker welfare under an isoelastic labor supply curve. Examples of such an organization would be the same bodies within state and local governments that introduce and enforce existing minimum wages for utilized hours in the gig economy.

In *period two*, the platform selects the price for an hour of ridesharing services to maximize its profits. They do this with knowledge of the commission rate cap from period one and subject to the equilibrium mechanics of the marketplace summarized in equation (2), and the optimal behavior of riders and drivers as embodied in the demand and supply functions $D(\bullet)$ and $H(\bullet)$, respectively.

Finally, in *period three*, the marketplace's participants make their decisions taking the commission rate and price as given, an equilibrium is reached, and outcomes are realized. Note that workers must necessarily be better off because the organization can always implement the commission rate that the platform would have wanted to implement.

Backward induction solves the game between the platform and the organization in the following steps. The platform's optimal choice of price given a commission rate in equation (4) implies that

$$\varepsilon_{p,\theta} = \frac{\theta}{1-\theta-\tau}. \tag{18}$$

where $\varepsilon_{p,\theta} = \frac{\partial p}{\partial \theta} \cdot \frac{\theta}{p}$. Next, I solve for the commission rate that maximizes workers' wages. The organization's optimization problem is subject to two constraints. First, utilization will respond to bring the market to equilibrium, which affects wages. Second, the organization internalizes the platform's optimal pricing response to changes in the commission rate with the best response function $P(\theta)$. 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

$$1 + \varepsilon_{p,\theta} - \tilde{\varepsilon}_{x,\theta} = 0, \tag{20}$$

The term $\tilde{\varepsilon}_{x,\theta}$ differs from $\varepsilon_{x,\theta}$, which is defined in equation (6), because the union internalizes the best response of the platform in the equilibrium condition. Now, this elasticity equals

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

Theorem 4 (Drivers' optimal commission cap)**.** *The commission rate that maximizes drivers' wages is*

$$1 - \theta^{**} = 1 - (1-\tau) \cdot \left(\frac{1}{\varepsilon_{D,p}} + \frac{\varepsilon_{D,x}}{\varepsilon_{D,p}} \right). \tag{22}$$

Proof. This follows from plugging equations (21) and (18) 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. Rather than marking up the commission rate according to the labor supply elasticity, the optimal cap reduces the commission rate depending on the elasticity of demand to price. The organization knows the platform will increase prices if the commission rate falls. Consequently, when passengers are insensitive to prices, the organization lowers the commission rate anticipating both that the platform will increase prices and that this will be largely tolerated by riders.

Theorem 5 (The optimal commission cap)**.** *The drivers's optimal commission rate, which is described by equation* (22)*, is the social planner's first best commission rate under perfect competition for passengers.*

Proof. Equation (22) converges to equation (17) under perfect competition for passengers. □

Driver wages and welfare. Translating changes in driver wages to welfare effects requires two considerations. First, driver preferences. Under the assumption of an isoelastic labor supply function, drivers' surplus in this market equals

$$U(w) = \frac{w \cdot H(w)}{1 + \varepsilon_{H,w}}. \tag{23}$$

Increases in the wage rate benefit workers directly and via the number of hours worked on the platform. The latter mechanism is especially pertinent in a labor market characterized by free entry. The change in welfare due to an exogenous change in the commission rate, which is of primary interest in the counterfactual here, is given by

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

where $\varepsilon_{U,\theta} = \frac{dU}{d\theta} \cdot \frac{\theta}{U}$. In turn, changing the rate of commission affects wages through a number of channels, as shown by the elasticity of wages to the commission rate

$$\varepsilon_{w,\theta} = 1 + \varepsilon_{P,\theta} - \tilde{\varepsilon}_{x,\theta}, \tag{25}$$

where $\varepsilon_{w,\theta} = \frac{dw}{d\theta} \cdot \frac{\theta}{w}$. Reducing the commission rate mechanically increases wages as workers keep a larger share of revenue, it raises prices due to the platform's behavioral response, which has an ambiguous effect on wages through its equilibrium consequences, and it encourages higher driver supply reducing utilization.

Second, earnings from the gig economy make up only a fraction of workers' overall income, typically around one-quarter (Anderson et al., 2021). Changes to total worker welfare can be approximated by multiplying the percentage change in worker surplus from gig work by the share of overall income earned in the gig economy (Christensen and Osman, 2023), assuming quasi-linear utility and that the elasticity of labor supply to other activities is similar.

3.2 A Minimum Wage on Utilized Hours

This subsection considers setting a minimum wage for workers' utilized hours (MWUH). Such policies have been popular amongst state and local policymakers (*e.g.*, see Seattle and Minneapolis) because, unlike traditional minimum wages, they do not require knowledge of workers' platform-specific labor supply. Denoting the level of the MWUH with $\bar{w}$, such a policy ensures that $p \cdot \theta$ does not fall below $\bar{w}$.

To evaluate the impact of this policy, I study raising $\bar{w}$ marginally above the utilized wage rate $p^* \cdot \theta^*$ that prevails in the *status quo* equilibrium. The impact of this policy on wages is summarized by

$$\varepsilon_{w^*,\bar{w}} = 1 - \varepsilon_{x,\bar{w}}, \tag{26}$$

where $w^* = p^* \cdot \theta^* \cdot x$ and $\varepsilon_{x,\bar{w}} = -\frac{dx}{d\bar{w}} \cdot \frac{\bar{w}}{x}$. That is, the MWUH mechanically raises drivers' equilibrium wages one-to-one but also leads to an offsetting change in the equilibrium level of utilization.

To calculate the magnitude of the offsetting effect, it is necessary to characterize the equilibrium response of utilization. The elasticity of utilization to the MWUH $\varepsilon_{x,\bar{w}}$ can be expressed in terms of behavioral elasticities after differentiating the equilibrium condition with the MWUH substituted in

$$D\left(\frac{\bar{w}}{\theta}, x\right) = x \cdot H(\bar{w} \cdot x), \tag{27}$$

which gives

$$\varepsilon_{x,\bar{w}} = \frac{\varepsilon_{D,p} \cdot (1 - \varepsilon_{\theta,\bar{w}}) + \varepsilon_{H,w}}{1 + \varepsilon_{H,w} + \varepsilon_{D,x}}, \tag{28}$$

where $\varepsilon_{\theta,\bar{w}} = \frac{d\theta}{d\bar{w}} \cdot \frac{\bar{w}}{\theta}$. Equation (28) contains the elasticity of the commission rate to the minimum wage, which captures the platform's pricing response to the MWUH alongside the broader equilibrium adjustments.

Characterizing the platform's reaction with behavioral elasticities requires solving their problem. The platform's optimization problem is now

$$\max_{p,\theta} \left[p \cdot (1-\theta) - c\right] \cdot D(p,x) \text{ subject to } D(p,x) = x \cdot H(p \cdot \theta \cdot x) \tag{29}$$
$$\text{and } \bar{w} = p \cdot \theta.$$

Platform optimization implies that

$$1-\theta^{\dagger}=1-\frac{\bar{w}}{c+\bar{w}}\cdot(1-\tau)\cdot\frac{\varepsilon_{D,p}-\varepsilon_{D,x}\cdot\check{\varepsilon}_{x,\theta}-1}{\varepsilon_{D,p}-\varepsilon_{D,x}\cdot\check{\varepsilon}_{x,\theta}}, \tag{30}$$

where

$$\check{\varepsilon}_{x,\theta}=\frac{dx}{d\theta}\cdot\frac{\theta}{x}=\frac{\varepsilon_{D,p}}{1+\varepsilon_{H,w}+\varepsilon_{D,x}}, \tag{31}$$

which comes from totally differentiating equation (27) with respect to x and θ. The dagger notation denotes the platform's endogenous choices in this new environment. Solving for prices readily follows from substituting equation (30) into the minimum wage constraint $p^{\dagger}=\frac{\bar{w}}{\theta^{\dagger}}$.

Theorem 6 (Worker welfare improving minimum wage on utilized hours.)**.** *The minimum wage on utilized hours leaves workers better off if and only if*

$$c+\bar{w}<\frac{1}{1-\frac{1+\varepsilon_{D,x}}{\varepsilon_{D,p}}}. \tag{32}$$

Proof. This follows from setting equation (26) greater than zero, recognizing that $\varepsilon_{\theta,\bar{w}}=\frac{1}{c+\bar{w}}$ from equation (30), and substituting in. □

Unlike a commission cap, a MWUHis not necessarily beneficial for workers. However, it is more likely to be so the when platform's market power over passengers is strong. The righthand side of inequality (32) equals the platform's markup on rider prices above marginal cost. Intuitively, platforms would rather increase the price than give a larger share of revenue to drivers. Therefore, when the platform's monopoly power is high, price increases do not reduce utilization too much, and drivers are left better off at the expense of riders.

3.3 Discussion

These results have practical implications for policymakers who are currently, or considering, intervening in gig labor markets with the goal of raising worker welfare. With respect to minimum wages on utilized hours, these policies are only effective if their mechanical benefit to workers is not outweighed by equilibrium adjustments in utilization. The results above clarify that this is the case when demand is not sensitive to price, which can be for two reasons. First, because platforms have monopoly power over consumers. Second, if passengers care greatly about waiting times, then price increases do not dampen demand too much because of an associated reduction in congestion.

Consequently, the model highlights three attractive features of commission caps. First, they can raise welfare regardless of the competitive state of the passenger market. Second, if the passenger market is competitive, policymakers can rely on the intelligence of market participants—in particular, drivers—to inform the optimal level of commission since their incentives are aligned with the social planner.[18] Third, if this is not the case, then given control of commission caps, the policymaker can induce sufficient variation to identify the optimal policy analogously to the empirical analysis below.

4 An Application to Uber

In this section, I use the model from section 2 to evaluate the extent of monopsony power enjoyed by the US's largest ridesharing platform, Uber. The model's parsimonious structure facilitates this analysis using only publicly available data and causal estimates from the academic literature. The results suggest that Uber enjoys substantial monopsony power over drivers but faces a competitive market for riders. Motivated by the results in section 3, setting the commission rate to its first-best level increases wages by 14 percent. Conversely, a minimum wage on utilized hours likely harms 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 75 percent. Currently, Uber has 1.5 million earners on its platform in the US. In most areas, workers are free to join and leave the platform, and once they are on the platform, drivers pick where and when to work.[19] Drivers can also work simultaneously for Uber's competitors, like Lyft, giving rise to issues in the measurement of platform-specific labor supply.

[18]Further, if the passenger market is competitive (*i.e.*, the demand elasticities are very high), then the policymaker need not be concerned about the welfare of passengers. This follows from the fact that rider surplus is $\frac{p \cdot D(p,x)}{\varepsilon_{D,p}-1}$, which equals zero under perfect competition for riders independent of prices.

[19]A notable exception is New York, where the city has implemented a myriad of regulations affecting platform pricing and the onboarding of drivers.

Given the available data, the focus of the analysis in this paper is Uber's US ridesharing marketplace around 2017. During this time, passenger fares were determined by time, distance, and Uber's surge algorithm. Two components determined fares: 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 rate, was deducted. All the booking fees went to Uber to cover the costs of mediating the ride. Tipping was only introduced in mid-2017 and was very rare at this time (Chandar et al., 2019).

Uber, as a *global* company, became profitable in 2023 after significant cost-cutting and divestments (*e.g.*, from developing its own autonomous vehicles and from its ridesharing business in Singapore). Losses due to these factors are largely unrelated to the performance of the firm's ridesharing marketplace in the US. Moreover, the platform's US market is its most mature and responsible for approximately two-thirds of the firm's revenue. Consequently, treating Uber's pricing as profit-maximizing is both plausible *ex ante* and matches the platforms behavior well *ex post*, as shown in the out-of-sample tests in section 4.4.

4.2 Data

Three empirical moments are necessary 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, which relates to these parameters via equation (9). This number is the subject of significant discussion, which is often confused by the coexistence of the booking fee for passengers and 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 passenger 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.[20] 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

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

of the booking fee from drivers during that period of time,[21] 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 booking fee, implies an average price per trip of $11.40.

Overall, these numbers constitute a commission rate of 34 percent, which I use as the central scenario in the analysis below.[22] I also consider commission rates of 29 percent and 39 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.

The second empirical moment is the price Uber charges for an hour of ridesharing services, connecting to participants' behavioral elasticities through equation (8). Combining the average price per trip of $11.40 with the average length of a trip produces this number. Fortunately, Cook et al. (2021) reports the average trip speed and distance, which jointly suggest a typical length of just over fifteen minutes. In turn, this suggests a price of $43.59 for one hour's worth of ridesharing services.

Theoretically, behavioral elasticities and costs comprise the price Uber charges. Consequently, information on Uber's costs is also required for the estimation. The main marginal costs to mediating exchanges are transaction fees for payment processing, 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 comprise 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 pick up, this suggests that insurance costs make up 15 percent of the passenger fare. In total, costs comprise 18 percent of the typical fare. 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. I assume these stem from changes in insurance costs, which have been volatile over time.

The third and final empirical moment is the equilibrium response of utilization to a change in price, which links to the model's parameters through equation (6).[23] Hall

[21] See discussion here.

[22] The choice of commission rate is also supported by Uber's breakdown of gross bookings in this blog post.

[23] Equation (7) characterizes the equilibrium response of utilization to a change in the commission rate and would provide an over-identifying restriction. Unfortunately, I am not aware of any estimates of this statistic. A related moment is the response of utilization to the introduction of tipping in Chandar et al. (2019). It is possible to conceive of tipping as a decrease in the commission rate; a greater portion of the passenger's payment goes to drivers. Consistent with the results below, Chandar et al. (2019) finds almost no response to utilization to a change in the commission rate.

et al. (2023) report static and dynamic estimates of this statistic, which exploit randomized pricing experiments by the platform. That is, they estimate the *causal* effect of prices on equilibrium utilization. Given that base 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 comes from price experiments in 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 platform-specific 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

$$\varepsilon_{x,p} \approx \hat{\varepsilon}_{x,p} + \frac{\partial \varepsilon_{x,p}}{\partial \varepsilon_{H,w}} \cdot (\varepsilon_{H,w} - \hat{\varepsilon}_{H,w}) = \hat{\hat{\varepsilon}}_{x,p}, \tag{33}$$
$$\text{where} \quad \frac{\partial \varepsilon_{x,p}}{\partial \varepsilon_{H,w}} = \frac{1 - (\varepsilon_{D,p} - \varepsilon_{D,x})}{(\varepsilon_{D,x} + 1 + \varepsilon_{H,w})^2},$$

where $\hat{\varepsilon}_{x,p}$ is the elasticity of utilization with respect to price measured using online hours. 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 above with further data on the average number 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 \$14.72, a utilization rate of 51 percent,[24] and a utilized wage rate of \$28.96. This is on the high side of Uber's reported earnings per utilized hour, which suggests that the statistics above do not offer a particularly negative picture of drivers' earnings.[25]

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 $\hat{X} = (\widehat{1-\theta}, \;\; \hat{p}, \;\; \hat{\hat{\varepsilon}}_{x,p})$ and the model's predictions from equations (6), (8), and

[24] This utilization rate only includes time with passengers and corresponds to x in the model.
[25] See this blog post again.

	Data moment	Model prediction
Commission rate	0.34	0.34
Price	43.59	43.53
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.

(9) using the norm $m(\hat{X}, \boldsymbol{\varepsilon})^T \cdot W \cdot m(\hat{X}, \boldsymbol{\varepsilon})$, where

$$m(\hat{X}, \boldsymbol{\varepsilon}) = \begin{pmatrix} \widehat{(1-\theta)} - 1 - (1-\tau) \cdot \frac{\varepsilon_{D,x}}{\varepsilon_{D,p}} \cdot \frac{\varepsilon_{H,w}}{1+\varepsilon_{H,w}} \\ \hat{p} - \frac{1}{1-(\frac{1}{\varepsilon_{D,p}} + \frac{\varepsilon_{D,x}}{\varepsilon_{D,p}})} \cdot \frac{\hat{c}}{1-\hat{\tau}} \\ \hat{\hat{\varepsilon}}_{x,p} - \frac{\varepsilon_{D,p}+\varepsilon_{H,w}}{\varepsilon_{D,x}+1+\varepsilon_{H,w}} \end{pmatrix}, \tag{34}$$

and W is the weighting matrix.[26] Although the model is just identified, weighting is helpful because of the finite sample.

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 (Hall et al., 2023). Therefore, these standard errors reflect only statistical uncertainty from the empirical estimate of the elasticity of utilization to price. Still, I refer to this procedure as estimation because it incorporates some statistical uncertainty, although, in practice, it is very close to a calibration exercise. The sensitivity of results to the commission rate and markup is assessed 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 the finite sample and sign restrictions on the elasticities. Further, other empirical models have

[26] I weight the moments according to either the inverse of their estimated variance, in the case of $\hat{\varepsilon}_{p,x}$, or by the inverse of an educated guess at their variance. I derive the latter by assuming that costs (as a share of the fare) and the commission rate have a standard deviation of two percentage points.

not been able to reconcile Uber's behavior purely with profit maximization (Castillo, 2023; Rosaia, 2020).

Differences between short- and long-run behavioral elasticities can explain this issue. Short-run elasticities that exploit variation in surge pricing, or experiments that last less than a few weeks, are generally small. Therefore, when they are used to inform long-run passenger and driver behavioral responses, these agents appear inelastic, which suggests that Uber has a lot of market power and should charge higher prices. Other long-term pricing experiments on the Uber platform have found much larger elasticities (Christensen and Osman, 2023), which are consistent with the results here.

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.[27] 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. 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.[28] In response, Uber raised prices by 40 percent.[29]

Interpreting this through the model, it is possible to map Uber's price response to how the policy affected drivers' utilized earnings. Equation (30), in combination with the minimum wage constraint, implicitly describes the platform's optimal price. The elasticity of prices to the minimum wage on utilized hours equals 0.90, when evaluated at the calibrated level of costs and existing utilized wage rate. Therefore, Uber's price response indicates the policy raised utilized wages by 45 percent. Uber do not report this number for Seattle, but the platform estimates that its labor costs will rise by up to 40 percent in the face of similar proposals in Minnesota,[30] which are less tough than those for Seattle at the time.

If the ordinance raised utilized wages by 45 and prices increased by 40 percent, then the platform would have to raise commission rates by five percent or, equivalently, three percentage points. A small increase in commission rates is consistent

[27] I do not use this event to provide over-identifying restrictions for the estimation because it occurred four years after the other data moments.

[28] 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

[29] See this Uber blog post.

[30] 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%	$\frac{\varepsilon_{D,x}}{\varepsilon_{D,p}} = 0.84 \ (<0.01)$	$\frac{\varepsilon_{\mathbf{D,x}}}{\varepsilon_{\mathbf{D,p}}} = \mathbf{0.84} \ (<\mathbf{0.01})$	$\frac{\varepsilon_{D,x}}{\varepsilon_{D,p}} = 0.84 \ (<0.01)$
		$\varepsilon_{H,w} = 2.92 \ (0.01)$	$\varepsilon_{\mathbf{H,w}} = \mathbf{4.27} \ (\mathbf{0.02})$	$\varepsilon_{H,w} = 6.37 \ (0.03)$
	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.

with the model, which predicts that Uber would respond to the policy primarily through price adjustments rather than changes in commission. Taking the price and commission rate changes together, utilization would fall by 56 percent, causing overall wages to fall by 11 percent. Uber reports that wages per online hour fell by ten percent,[31] again, 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, Seattle's minimum wages on utilized hours does not seem to have benefited workers. I evaluate the efficacy of these policies in the US more generally in section 5.2.

4.5 Results

Table 2 shows parameter estimates for nine different combinations of Uber's commission rate and costs. This provides greater transparency to the reader, who can decide for themselves the level of uncertainty in commission rates and costs—and the extent to which this uncertainty is correlated. As a guide, the central scenario is highlighted in bold in the middle of the matrix. I find the most likely deviations from

[31] See this Uber blog post again.

this to be the off-diagonal elements. In other words, costs and commission rates are either likely to be positively correlated (*i.e.*, Uber takes more from drivers when they face higher mediation costs) or uncorrelated, but not negatively correlated.

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 is remarkably similar to estimates of monopsony power in other US labor markets despite the very different modeling and estimation approach (Lamadon et al., 2022). The estimate of monopsony power decreases if the platform is considered to charge a higher commission rate and rises if Uber is believed to face higher costs. All the estimates imply a considerable degree of monopsony power unless one maintains the implausible assumption that Uber has *both* an unlikely high level of costs and low commission rate.

In contrast, all of the 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 $\frac{\varepsilon_{D,x}}{\varepsilon_{D,p}}$. This approximately equals the driver's keep rate (*i.e.*, one minus the commission rate) under a perfectly competitive driver market.[32] The fact that all these ratios all but 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 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 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. In section 5, I explore the impact of Uber's monopsony power on wages and welfare by considering feasible counterfactuals that account for equilibrium effects.

5 Counterfactuals

This section studies two counterfactuals to quantify how monopsony power affects wages and, in turn, worker welfare in a two-sided ridesharing market. Specifically, I study a commission cap set to maximize driver wages and a minimum wage for workers' utilized hours. In doing so, I also present the predicted impact on wages of

[32]When multiplied by $(1-\tau)$, which is close to one, this mapping is exact.

		Commission rate		
		39%	34%	29%
	13%	$\%\Delta w = 34$ $\%\Delta U = 29$	$\%\Delta w = 23$ $\%\Delta U = 24$	$\%\Delta w = 16$ $\%\Delta U = 21$
Costs	18%	$\%\Delta w = 23$ $\%\Delta U = 23$	$\%\mathbf{\Delta w} = \mathbf{14}$ $\%\mathbf{\Delta U} = \mathbf{18}$	$\%\Delta w = 8$ $\%\Delta U = 14$
	23%	$\%\Delta w = 14$ $\%\Delta U = 17$	$\%\Delta w = 7$ $\%\Delta U = 12$	$\%\Delta w = 2$ $\%\Delta U = 8$

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.

restoring Uber's market for drivers to perfect competition.

5.1 Commission Caps

Given the analysis in section 3, I consider setting the commission rate equal to its socially efficient level, as defined in equation (17), and allowing the platform to respond with passenger prices. Policymakers can feasibly implement this policy in many ways. For example, given control of the commission rate, they can induce sufficient variation to infer an optimal commission cap, and, if the passenger market is competitive, they can use information from drivers to determine the optimal rate as shown in theorem 5. Moreover, existing pricing regulations in this labor market indicate a commission cap is both legally and politically feasible.

Using equations (24) and (25), table 3 presents estimates of the impact of monopsony power on wages w and the aggregate worker surplus U, where the latter has been scaled down to account for gig work's tendency to be a secondary source of income.[33] The central estimate in bold implies that drivers' wages would rise by 14 percent in equilibrium, or \$2.00 per hour. It is possible to decompose this change in wages using

[33] I assume earnings from the gig economy comprise one-quarter of an individual's income.

equation (25) as follows

$$\%\Delta w = \left[1 + \underbrace{(1-\varepsilon_{x,p})\cdot\varepsilon_{P,\theta}}_{\text{(1-1.18)}\times\text{2.17=-0.40}} - \underbrace{\varepsilon_{x,\theta}}_{\sim 0}\right]\cdot\underbrace{\%\Delta\theta}_{0.23} \approx 14. \tag{35}$$

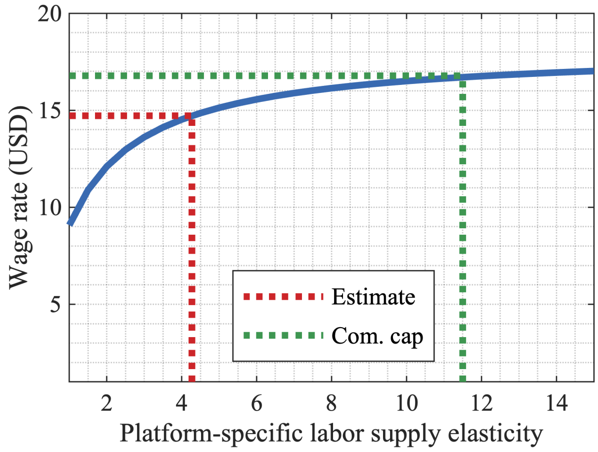
Pricing responses by the platform and equilibrium adjustments in utilization mediate the effect of changes in the commission rate on wages. The elasticity of the platform's price to the driver's keep rate is 2.17, as computed from equation (18). This has a further positive effect on drivers' wages *ceteris 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.

One way to benchmark these wage changes is to compare their magnitude with equivalent changes in Uber's platform-specific labor supply elasticity. Figure 1 illustrates this idea by tracing out workers' wages as a function of this parameter. Attaining the wage gains that occur under the commission cap scenario requires almost tripling Uber's platform-specific labor supply elasticity, which would entail a dramatic change in the competitive landscape of the US ridesharing market.

Table 3 also reports the overall effect on the surplus that drivers derive from Uber's ridesharing marketplace. These estimates rely on stronger assumptions than the predicted wage changes since they require drivers' behavioral elasticities to be fully representative of preferences, and they also rest on assumptions about labor markets

Figure 1: Wages as a Function of the Platform-Specific Labor Supply Elasticity



Notes: This figure plots drivers' equilibrium wage rate in solid blue as a function of Uber's platform-specific labor supply elasticity, keeping demand-side elasticities constant. The dashed red line denotes the *status quo* equilibrium level of wages, and the dashed green line shows the level of wages attained in the commission cap counterfactual.

outside of the gig economy.[34] Nonetheless, the results indicate that a commission cap leads to large welfare gains for drivers. A 14 percent increase in wages raises the workers' total surplus by close to 18 percent. Naturally, the larger the wage change estimate, the greater the improvement in worker welfare. Significant welfare gains are due in part to gig work's flexibility; when wages increase, drivers can increase their hours freely to satisfy the intratemporal optimality condition.

5.2 A Minimum Wage on Utilized Hours

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 harms workers. Evaluating the left-hand side of inequality (32) at the *status quo* utilized wage and costs level equals 37, which exceeds the right-hand side of 6. This indicates there is no room to raise utilized wages in a way that increases equilibrium wages because they would trigger a fall in utilization, which more than offsets the positive direct effect on equilibrium wages. This is exemplified by the discussion of Seattle's *Fare Share* ordinance in section 4.4.

[34] In particular, scaling down welfare changes by the share of income that workers derive from ridesharing is appropriate if drivers' utility is quasi-linear and their labor supply elasticity to other labor markets is approximately the same as to ridesharing, which seems reasonable given similar estimates of elasticities to other industries (Lamadon et al., 2022).

In summary, the minimum wage is ineffective despite Uber's significant monopsony power. This type of minimum wage allows the platform to select its optimal price and commission rate mix while satisfying the minimum wage. The additional flexibility relative to a commission cap leaves the platform able to exploit its monopsony power, which can manifest in low utilization, as well as low utilized wages. Ultimately, the policy fails to target the welfare-relevant quantity: equilibrium wages.

6 Conclusion

This paper develops a tractable model of a typical gig labor market: ridesharing. The framework reveals how platforms use monopsony power over drivers to mark up commission rates according to the labor supply elasticity that they face. Consequently, estimates of firm-specific labor supply remain an appropriate way to measure monopsony power in the gig economy. However, the multi-sided nature of these markets complicates the final effect on workers' wages, as well as the impact on consumers. Bringing the model to the data, I find that the US's largest ridesharing platform, Uber, exerts substantial monopsony power and wages are 15 percent below the competitive benchmark.

I consider the role of feasible policies in ameliorating monopsony power in these labor markets. The efficacy of minimum wages on utilized hours, where policymakers mandate minimum payments to workers for time spent with customers, rests crucially on the capacity of the consumer market to absorb price increases. If price increases significantly reduce demand, then these policies actually reduce equilibrium wages. I find that this is likely the case in the US ridesharing market, despite the policy's implementation across many state and local jurisdictions.

Conversely, commission caps provide a robust tool to raise worker welfare. The model reveals several favorable features of this policy. For example, given the power to set commission rates, policymakers can induce variation sufficient to identify the optimal cap. In addition, when the passenger market is competitive, drivers would collectively set the first-best commission rate if they had the choice. Therefore, since this paper's empirical results indicate that Uber faces strong competition for its customers, policymakers could be reliably informed by the intelligence of drivers when setting a commission cap.

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