Congestion Surcharge and Wage Regulation on TNCs: A Case Study for San Francisco

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Abstract

This paper studies the joint impact of congestion surcharge and wage regulation on transportation network companies (TNCs). These impacts are assessed by a market equilibrium model that captures the incentives of the passengers, drivers, and the platform, and accounts for the congestion externalities of the TNC vehicles. Under a wage floor on TNC drivers, we consider two schemes of congestion surcharges: (a) surcharge based on each TNC trip, and (b) surcharge based on each vehicle hour (regardless of whether the vehicle has a passenger or not). We show that both congestion surcharges can reduce the TNC ridership, but their impacts are mitigated by the wage floor and cannot significantly reduce the number of TNC vehicles. In contrast to the trip-based surcharge, we advocate the time-based congestion surcharge, which penalizes idle vehicle time and improves the vehicle occupancy. Through a case study for San Francisco, we show that the time-based congestion surcharge offers a Pareto improvement. It leads to higher passenger surplus, higher driver surplus, higher platform profits, and higher tax revenue for the city.

Keywords: TNC, wage floor, ride-sharing, regulatory policy.

1. Introduction

Transportation network companies (TNCs), such as Uber, Lyft and Didi, have profoundly transformed the urban transportation system. The on-demand mobility services offer an affordable alternative transport mode to public transit and private vehicles, in the meanwhile providing numerous job opportunities for drivers working as independent contractors. It is estimated that UberX alone generated $6.8B consumer surplus within the U.S. in 2015 \cite{uber}. 

Recently, the explosive growth of TNCs has raised several public concerns in large metropolitan areas. The first concern is on the traffic congestion due to the flooding of TNC vehicles. In New York City, Uber, Lyft, Juno and Via jointly dispatch nearly 600,000 rides per day, involving about 80,000 vehicles. Schaller \cite{schaller} reveals that during 2013-2017, TNC trips have increased by 15%, traffic speed reduced by 15%, VMT increased by 36%, and TNC vehicles increased by 59%. He suggested to reduce the unoccupied time of TNC vehicles in order to limit the city’s congestion. Another report \cite{sanfrancisco} by San Francisco Transportation Authority provides information on the size, location, and time-of-day characteristics of TNC activities in San Francisco County. A follow-up report \cite{sanfrancisco2} identified the impact of TNC activities on traffic congestion and showed that TNCs account for approximately 50 percent of the increase in congestion in San Francisco between 2010 and 2016. More recently, Uber and Lyft have commissioned Fehr & Peer to estimate the

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TNC share of VMT in six US Metropolitan Regions, including Boston, Chicago, Los Angeles, Seattle, San Francisco and Washington. The report [5] shows that Uber and Lyft have a heavy traffic impact in core urban areas such as San Francisco County, where they account for 13.4% of all vehicle-miles.

The second concern is on the sub minimum-wage earning of TNC drivers. The success of the on-demand ride-hailing business relies on a very short passenger waiting time, which in turn depends on a large number of available but idle TNC drivers. This generally leads to a low driver wage. Parrott and Reich [6] revealed that the majority of the for-hire vehicle drivers in New York City work full-time. They estimated that 85 percent of drivers make less than the minimum wage after deducting the vehicle expenses, and the median driver earning has declined by almost $3 per hour from $25.67 in 2016 to $22.90 in 2017. These drivers are hired as independent contractors, who can not unionize to negotiate for labor rights such as minimum wage, overtime compensation, and paid time-off.

The aforementioned concerns have prompted the cities to take actions to regulate TNCs. To address congestion, the New York City Taxi and Limousine Commission has imposed a cap on cruising [7] and introduced a $2.75 surcharge for all for-hire vehicles that pass through the “congestion zone” of the city [8]. The congestion zone is defined as the south of 96th street in the borough of Manhattan, and the surcharge is assessed on each trip by for-fire vehicles that starts from, ends in, or passes through the congestion area. To protect TNC drivers, New York City (NYC) demands a minimum per-trip wage for drivers that amounts to a wage floor of $25.76/hour or $17.22/hour after expenses [9]. Similar rules around TNC regulations are also considered in other cities in the U.S.. For instance, Chicago has approved traffic congestion tax on ride-hailing services for weekday trips in downtown area [10]. San Francisco proposed a surcharge on TNC rides to raise fund for congestion mitigation projects [11]. California passed bill AB5 [12] that labels hundred of thousands of independent contractors including TNC drivers as employees to protect them with minimum wage and other employee benefits. These actions imply a changing regulatory environment to address TNC externalities in large cities.

Motivated by recent regulatory environment, this paper presents a model to evaluate the joint impact of congestion surcharge and wage regulations on TNCs. Our model endogenously captures the arrival of passengers, the number of drivers, and the ride prices given the exogenous regulatory policies. It consists of a queuing theoretic model that captures the dynamic arrivals of passengers and drivers, a general equilibrium that predicts the impact of market prices and payments on passengers and drivers, and an optimization model that captures the platform decision making. This framework enables us to assess the policy impacts on various aspects of the TNC market, including ride prices, passengers waiting times, driver wage, number of passengers and drivers, occupancy rate, platform rent, city tax revenue, among others. The key contributions of this work are summarized below:

- We evaluated the joint impacts of congestion surcharge and wage regulation on TNC. We show that congestion surcharge will reduce the TNC ridership, but surprisingly, the impact of congestion surcharge is mitigated by the wage floor on TNC drivers, and therefore cannot significantly reduce the number of TNC vehicles on the road. This is due to the TNC labor market power.

- We compared two schemes of congestion surcharges: (a) surcharge based on each TNC trip, and (b) surcharge based on each vehicle hour (regardless of whether the vehicle has a passenger or not). We show that time-based congestion surcharge penalizes idle vehicle hours and improves the vehicle occupancy. Furthermore, the increase of occupancy generates surplus that offers a Pareto improvement to benefit all stakeholders: it can lead to higher consumer surplus, higher driver surplus, higher platform profit and higher tax revenue for the city.

- We presented a realistic case study for San Francisco. We calibrated the model parameters to match the reported San Francisco TNC data, and used the model to predict the likely effect of regulatory policies on the San Francisco TNC market.
**Related Works:** The studies on app-based ride-hailing platforms are extensive. Many of these works capture the passengers incentives, driver incentives, service delay, and platform pricing. Banerjee [13] developed a queuing theoretic model to study the optimal pricing of ride-sharing platforms. They showed that the performance of dynamic price (in terms of revenue and throughput) does not exceed that of the static price, but it is more robust to fluctuations of model parameters. Bai [14] considered the on-demand service platform using earning-sensitive independent providers with heterogeneous reservation price, and concluded that it is optimal to charge a higher price when demand increases, and that the platform should offer a higher payout ratio as demand increases, capacity decreases or customers become more sensitive to waiting time. Taylor [15] studied how delay sensitivity and agent independence impact the platform’s optimal price and wage, and identified the complexity when there is uncertainty in the customers’ valuation. Aside from platform pricing, many other works touch upon driver supply [16], [17], platform operations [18], [19], platform competition [20], [21], and regulations [22], [23], [24]. Please refer to [25] for a comprehensive literature review.

Road pricing has attracted substantial research attention for decades. The idea was initially proposed by Pigou [26], which inspired several seminal works including Vickery [27], Walters [28] and Beckmann [29]. Since then, various pricing schemes have been proposed in the literature. These include surcharges based on cordon crossing, distance traveled, time spent traveling, or tolls in congestion [30]. For instance, Zhang and Yang [31] investigated the cordon-based second-best congestion pricing problem on road networks that jointly consider toll levels and toll locations. Yang et al [32] studied road pricing for effective congestion control without knowing the link travel times and travel demand. Liu and Li [33] derived a time-varying toll combined with a flat ride-sharing price to nudge morning travelers to depart in off-peak hours. Despite this vast literature in transportation and economics, the research in congestion surcharge for TNC is relatively scarce. Congestion surcharge for TNC is distinct since it involves decisions making of the profit-maximizing platform and the passengers and drivers in the two-sided ride-hailing market.

There are only a handful of works on the regulation of TNCs. Gurvich [34] studied the platform’s profit maximizing wage level for self-scheduling drivers, and showed that under a minimum wage, the platform limits agent flexibility by restricting the number of agents that can work in some time intervals. Parrott and Reich [6] utilizes the administrative data of New York City and showed by simulation that the proposed minimum wage standard in New York City will increase driver wage by 22.5 percent while hurting the passengers by slightly increasing the ride fare and passenger waiting time. Zhang and Nie [35] considered a ride-sharing platform offering a mix of pool and solo rides and evaluated the impact of regulation policies on the platform operation. Yu et al. [24] studied the impacts of entry limit on TNCs considering the interactions between TNCs and taxis, and showed that carefully designed entry limit can achieve a balance between competing regulatory objectives. Li [22] and Benjaafar [23] developed market equilibrium models to show that wage regulations on TNC will benefit both passengers and drivers, and this is because the wage regulation curbs the TNC labor market power [22].

In the literature, the closest work to ours is that in [22] and Schaller [36]. In [22] a market equilibrium model was proposed to evaluate the impact of various regulatory policies on TNC systems. This paper differs from [22] since (a) we consider congestion externalities of TNC vehicles, (b) we focus on the joint impacts of congestion surcharge and wage regulation, and (c) we compare different schemes of congestion surcharges. In Schaller [36] it is recommended that congestion surcharge be levied as an hourly charge rather than a per-trip charge because hourly charge provides strong incentives for the passengers to use shared ride services and for the platform to reduce the time between trips without a passenger. This recommendation is consistent with the results in our paper. However, our paper differs from Schaller [36] in that we provide a mathematical formulation to justify this conclusion.
2. TNC Environment

We consider a transportation system with a city council, a TNC platform, and a group of passengers and drivers. The city council establishes legislation (e.g., cap on the total number of cars, minimum wage on TNC drivers, congestion surcharge on TNC trips, etc) to regulate the operations of the TNC platform. Under these policies, the platform makes pricing decisions to maximize its profit. The pricing decisions will affect the choices of passengers and drivers. For instance, each passenger may have multiple mode choices and makes transport decisions by comparing the waiting time and ride fares of different modes. Similarly, drivers have multiple employment opportunities and choose the job that offers the highest wage. Collectively, these individual decisions will affect the profit of the platform, and they collectively constitute the market equilibrium, which is affected by regulatory policies.

3. Market Equilibrium Model

This section presents the market equilibrium model that captures the decision making of individual passengers and drivers. The model is used to predict the long-term average of passenger and driver arrivals under fixed platform ride prices and driver wages.

3.1. Matching passengers and drivers

Consider a transportation market with randomly arriving passengers served by $N$ TNC drivers. Upon arrival, each passenger immediately joins a queue and waits until he is matched to an idle driver. This can be captured as a continuous-time queuing process, where each passenger defines a “job” and each driver corresponds to a “server”. The server is “idle” if the vehicle is not occupied, and is “busy” if a passenger is on board or is assigned a passenger and on its way to pick her/him up. By assuming that the arrival process of passengers is Poisson with rate $\lambda > 0$, we can model this process as an $M/G/N$ queue, where the expected number of idle servers (vehicles) is $N_I = N - \lambda/\mu$, and $\mu$ is the service rate.

3.2. Passenger incentives

Passengers choose transport mode based on the travel cost for available options including TNC, public transit, walking, biking, etc. Assume the travel cost of TNC is the weighed sum of time and money:

$$c = \alpha t_w + p_f,$$

where $t_w$ is the waiting time and $p_f$ is the average price of TNC ride. The model parameter $\alpha$ specifies the passenger trade-off between time and money. A TNC ride consists of three periods: (1) from the ride being requested to the ride being confirmed, (2) from the ride being confirmed to the passenger pickup, (3) from passenger pickup to drop-off. Let $t_m$, $t_p$, and $t_o$ represent the length of these three periods, respectively. By definition, we have $t_w = t_m + t_p$, and it is clear that $t_o$ is the average trip distance $L$ divided by traffic speed $v$, i.e., $t_o = L/v$. Since the platform immediately matches each newly arrived passenger to her nearest idle vehicle, $t_m$ is the average waiting time in the queue, and $t_p$ depends on the traffic speed $v$ and the distance of the passenger to the nearest idle vehicle, which further depends on the number of idle vehicles $N_I$. Therefore, we can write $t_p$ as a function of $N_I$ and $v$, i.e., $t_p(N_I, v)$. The following assumptions are imposed on $t_p(\cdot)$:

\footnote{For simplicity, we do not consider the case of multiple passengers sharing the same ride.}
Assumption 1. Assume that \( t_p(N_I, v) \) is twice differentiable with respect to \( N_I \) and \( v \). It is decreasing and strictly convex with respect to \( N_I \), and it is decreasing with respect to traffic speed \( v \).

Assumption 1 requires that the pickup time decreases with respect to the number of idle vehicle and with respect to the traffic speed. We model traffic speed as a function of the number of cars \( v(N) \) and impose the following assumption on \( v(\cdot) \):

Assumption 2. Assume that \( v(N) \) is decreasing and continuously differentiable with respect to \( N \).

Typically, the ride confirmation time \( t_m \) is below 30 seconds, the pickup time \( t_p \) is 3-5 minutes. Therefore, we ignore \( t_m \) and derive the total waiting time \( t_w \) as:

\[
 t_w = t_p(N_I, v).
\] (2)

Passengers choose their transport modes based on the total travel cost. The arrival rate of TNC passenger is given by

\[
 \lambda = \lambda_0 F_p(c),
\] (3)

where \( \lambda_0 \) is the arrival rate of potential passengers (total travel demands in the city), and \( F_p(\cdot) \) represents the proportion of passengers who choose TNC. We assume that \( F_p(\cdot) \) is a strictly decreasing and continuously differentiable function so that higher TNC travel cost \( c \) indicates fewer passengers.

3.3. Driver incentives

Drivers are sensitive to earnings and respond to the offered wage by joining or leaving the platform. The average hourly wage of the TNC driver is:

\[
 w = \frac{\lambda p_d}{N},
\] (4)

where \( p_d \) is the average per-trip payment to drivers. The driver payment \( p_d \) is distinct from passenger trip price \( p_f \). The difference is kept by the platform as its commission or profit. The average hourly wage (4) is derived as follows. The total platform payment to all drivers sums up to \( \lambda p_f \), thus each driver receives \( \lambda p_f \) divided by \( N \). Each driver has a reservation wage. He joins the platform if the offered wage is greater than the reservation wage. We assume that the reservation wages of drivers are heterogeneous, and denote \( F_d(\cdot) \) as the cumulative distribution of reservation wages across the drivers. The number of TNC drivers willing to work for TNC is then given by

\[
 N = N_0 F_d(w),
\] (5)

where \( N_0 \) is the number of potential drivers (all drivers seeking a job), and \( F_d(w) \) is a strictly increasing and continuously differentiable function that represents the proportion of drivers willing to join TNC.

4. Profit Maximization under Trip-Based Congestion Surcharge

The platform determines the ride fare \( p_f \) and the driver payment \( p_d \) to maximize the profit per unit time (i.e., \( \lambda(p_f - p_d) \)). The optimal decisions of the platform depends on the exogenous regulatory policies imposed by the city. Here we consider a platform that maximizes the profit under a trip-based congestion surcharge and a wage floor on TNC driver earnings. The profit maximizing problem can be cast as follows:

\[
 \max_{p_f, p_d, N} \lambda(p_f - p_d)
\] (6)
\[
\begin{align*}
\lambda &= \lambda_0 F_p(\alpha t_p(N - \lambda/\mu, v) + p_f + p_t) \\ N &\leq N_0 F_d(\frac{\lambda p_d}{N}) \\ \frac{\lambda p_d}{N} &\geq w_0
\end{align*}
\]  

(7a) \quad (7b) \quad (7c)

where \( p_t \) is the congestion surcharge on each TNC trip, and \( w_0 \) is the wage floor on TNC driver earning. The inequality constraint (7b) indicates that the platform can choose not to hire all the drivers willing to work for TNC if the labor cost per driver is prohibitive due to the wage floor. Overall, the profit maximizing problem (6) is non-convex. However, since the dimension of the problem is small, we can efficiently solve (6) via brute-force enumeration.

4.1. Numerical example

We investigate the impacts of the proposed regulations via a case study for San Francisco (followed by theoretical analysis in the next subsection). Assume that passengers choose their transport modes based on the total travel cost. Under a logit model, the demand function is given as:

\[
\lambda = \lambda_0 \frac{e^{-\epsilon c}}{e^{-\epsilon c} + e^{-\epsilon c_0}}
\]  

(8)

where \( c \) denotes the travel cost of TNC, and \( \epsilon > 0 \) and \( c_0 \) are the model parameters. Similarly, drivers choose their employers based on their wage. Under a logit model, the supply function is given as:

\[
N = N_0 \frac{e^{\sigma w}}{e^{\sigma w} + e^{\sigma w_0}}
\]  

(9)

The passenger pickup time \( t_p \) satisfies the “square root law” established in [37] and [22]:

\[
t_p(N, v) = \frac{M}{v \sqrt{N - \lambda/\mu}},
\]  

(10)

where \( M \) is a constant depending on the characteristics of the city. The square root law establishes that the average pickup time is inversely proportional to the square root of the number of idle vehicles in the city. The intuition behind this result is simple: assume that all idle vehicles are uniformly distributed in the city, then the distance between any two nearby idle vehicles is inversely proportional to the square root of the total number of idle vehicles. This distance is proportional to the distance between the passenger and the closest idle vehicle, which determines the pickup time. The rigorous justification of the square root law can be found in [22].

The average traffic speed \( v \) is a function of \( N \). Using the Greenshied’s model in [38], we have a linear speed-density relation. Hence

\[
v = v_f - \kappa N
\]  

(11)

To summarize, the model parameters include:

\[
\Theta = \{\lambda_0, N_0, M, L, v_f, \kappa, \alpha, \epsilon, c_0, \sigma, w_0\}
\]

In this numerical study, we set the parameters values so that the optimal solution to (6) match the real data of San Francisco city. The values of these model parameters are summarised below:

\[
\lambda_0 = 944/\text{min}, \quad N_0 = 10000, \quad M = 40.8, \quad L = 2.6 \text{ mile}, \quad v_f = 16.8 \text{ mph}, \quad \kappa = 0.001.
\]

\[
\alpha = 3, \quad \epsilon = 0.26, \quad c_0 = 22.6, \quad \sigma = 0.12, \quad w_0 = \$33.57/\text{hour}.
\]
For detailed justification of these parameter values, please refer to Appendix A.

We solve the profit maximizing problem (6) for different congestion surcharge $p_t$ under a fixed wage floor $w_0$, and draw all the variables as a function of $p_t$. The minimum wage of TNC drivers in San Francisco is set in a similar way as that in NYC. In recent NYC regulations, the TNC driver minimum wage is set to $25.76$/hour, which is equivalent to the $15$/hour minimum wage of NYC after deducting the vehicle expenses (such as insurance, maintenance etc) and taxes. Since the hourly minimum wage of San Francisco is $0.59$ higher than that of NYC, we set $w_0 = 25.76 + 0.59 = 26.35$/hour to compensate for this difference.

4.2. Analysis

Figure 1- Figure 3 show the number of drivers, arrival rate of passengers, and the occupancy rate of the TNC market as a function of the congestion surcharge $p_t$ when the minimum wage is set at $w_0 = 26.35$/hour. Figure 4 shows the per-trip ride fare and driver payment. Figure 5-Figure 6 show the passenger pickup time and travel cost. Figure 7 shows the driver wage (which equals the minimum wage). Figure 8 and Figure 9
show the platform profit and city’s tax revenue under different values of $p_t$, respectively.

Clearly, the optimal solution as a function of $p_t$ has two distinct regimes:

- when $p_t \leq $3.89/trip, the number of driver remains constant, while the number of passengers reduces. The vehicle occupancy drops, the passenger pickup time decreases, the ride fare increases, and the passenger total travel cost increases. In the meanwhile, driver wage remains constant and equals the minimum wage, the platform profit reduces, and the tax revenue increases.

- when $p_t > $3.89/trip, both the passenger arrival rate and number of TNC drivers reduce sharply. The vehicle occupancy reduces, the ride fare and pickup time increase, and the total travel cost increases. The driver wage remains constant and equals the minimum wage, while the platform revenue reduces, and the tax revenue increases.

This is a surprising result: the number of drivers is unaffected by the congestion surcharge $p_t$ when $p_t \leq $3.89/trip. It is in stark contrast with the case where there is only congestion surcharge and the minimum wage constraint is lifted (see [22]). Therefore, this set of result indicates that contrary to the common belief, the effect of congestion surcharge on congestion relief is mitigated by the wage floor on TNC drivers. In certain regimes, the congestion surcharge can not directly curb traffic congestion by reducing the number of TNC vehicles.

The underlying reason behind this surprising result is rooted in the platform market power in the labor market. The platform is a monopoly the labor market and sets driver wages. When there is no regulations (i.e., $p_t = 0$ and $w_0 = 0$), the platform under-hires drivers to maximize its profit (compared to a competitive labor market where TNC faces the competitive driver wage). In certain regime, the minimum wage squeezes the platform’s market power and force the platform to hire more drivers [22]. This indicates that the marginal profit of hiring additional drivers under the minimum wage regulation is positive. When a congestion surcharge is insignificant, this marginal profit reduces but remains positive, and thus the platform still hires all drivers available in the labor market. The number of drivers are upper bounded based on $N \leq N_0 F_d(w_0)$. Therefore, in the first regime, $N$ remains constant and satisfies $N = N_0 F_d(w_0)$. If the congestion surcharge is further increased, the marginal profit of hiring an additional driver reduces to zero, and the system enters the second regime.

We can show that this quantitative result reported in Figure 1-Figure 9 (including number of drivers, number of passengers, platform revenue, and tax revenue) is robust for a large range of model parameters. For notation convenience, let $\tilde{w}$ be the optima driver wage for the platform without any regulation (i.e., $p_t = 0$ and $w_0 = 0$), and denote $N^*_t(p_t)$ as the optimal number of drivers to (6) under a fixed wage floor, which depends on $p_t$, then we have the following theorem

**Theorem 1.** Assume that (6) has a unique solution. For any model parameters $\lambda_0, N_0$, and $\alpha$, any strictly increasing function $F_p(c)$, any strictly decreasing function $F_d(w)$, any pickup time function $t_p$ that satisfies Assumption 1, and any speed-density relation $v(N)$ that satisfies Assumption 2, there exists $w_1 > \tilde{w}$, such that for any $\tilde{w} < w_0 < w_1$, there exists $\tilde{p}_t > 0$, so that $\nabla N^*_t(p_t) = 0$ for $\forall p_t \in (0, \tilde{p}_t)$.

The proof of Theorem 1 is can be found in Appendix B. It states that for any wage floor in an appropriate range, there is always a regime in which the congestion surcharge does not affect the number of TNC vehicles. Note that $w_2$ can be calculated numerically, and $\tilde{p}_t$ depends on the wage floor $w_0$. For the case of San Francisco, we derive that $w_2 = $28.95/hour and $\tilde{p}_t = $3.89/trip when $w_0 = $26.35/hour.
5. Profit Maximization under Time-Based Congestion Surcharge

This section considers the profit maximization problem under a wage floor and a time-base congestion surcharge, where each vehicle is charged based on the total time it stays active on the platform (regardless of whether there is a passenger on board or not). Let $p_h$ denote the per-vehicle per-unit-time congestion surcharge. The total surcharge (per unit time) is $Np_h$, and the profit maximization problem can be cast as:

$$\max_{p_f, p_d, N} \lambda(p_f - p_d) - Np_h$$

subject to:

$$\lambda = \lambda_0 F_p(\alpha t_p(N - \lambda/\mu, v) + p_f)$$

$$N \leq N_0 F_d\left(\frac{\lambda p_d}{N}\right)$$

$$\frac{\lambda p_d}{N} \geq w_0,$$

where $w_0$ is the wage floor of TNC drivers. To avoid triviality, we assume that (12) has at least on non-trivial solution.

**Remark 1.** The time-based congestion surcharge can be either imposed on the platform or on the individual drivers. We argue that these two formulations are equivalent after a change of variable. In practice, it may be more convenient for the city to collect this surcharge directly from the platform. In this case, the city only needs to periodically review the operational data of TNCs and enforce the charge on the platforms based on their aggregated vehicle hours.

5.1. Case study

We solve the profit maximization problem (12) for different time-based congestion surcharge $p_h$ under a fixed wage floor $w_0 = $26.35/hour. The model parameters of (12) are the same as those in Section 4.1.

Figure 10 - Figure 12 present the number of drivers, passenger arrival rates, and the vehicle occupancy as a function of the time-based congestion surcharge. Figure 13 shows the ride fare and per-trip driver payment. Figure 14 and Figure 15 show the passenger pickup time and total travel cost. Figure 16 shows the driver wage. Figure 17 and Figure 18 present the platform profit and tax revenue, respectively. Clearly, the results in Figure 10-18 have two distinct regimes:

- When $p_h \leq $9.54/hour, the number of TNC drivers and the passenger arrival rate remain constant. So is the occupancy rate, ride fare, per-trip driver payment, pickup time, passenger travel cost and driver wage. The platform revenue reduces linearly, and the tax revenue increases also linearly.

- When $p_h > $9.54/hour, the numbers of drivers and passengers reduce. The vehicle occupancy reduces. The ride fare and pay-trip driver payment also reduce. The pickup time and passenger travel cost increase. The driver wage is constant and equals the minimum wage. The platform profit reduces and the tax revenue increases.

Simulation results suggest that the time-based congestion surcharge does not affect the number of TNC vehicles unless it is greater than $9.54/hour. In this case, the effect of congestion surcharge on congestion relief is mitigated by the minimum wage on TNC drivers. This observation is consistent with the results in Section 4.2 due to the same reason. However, different from trip-based congestion surcharge, time-based surcharge does not affect the passenger rates (Figure 11). This indicates that time-based congestion
surcharge incurs a direct money transfer from the platform to the city in the first regime without affecting the passengers or drivers. This is evidenced by the linear curves in the first regime of Figure 17 - 18.

The quantitative results in Figure 10-Figure 18 are robust to the variation of model parameters. Formally, We denote $N^*_h(p_h)$ and $\lambda^*_h(p_h)$ as the optimal number of drivers and passenger arrival rates to (12) under the fixed wage floor, respectively, and introduce the following theorem:

**Theorem 2.** Assume that (12) has a unique solution. For any model parameters $\lambda_0$, $N_0$, and $\alpha$, any strictly increasing function $F_p(c)$, any strictly decreasing function $F_d(w)$, any pickup time function $t_p$ that satisfies Assumption 1, and any speed-density relation $v(N)$ that satisfies Assumption 2, there exists $w_2 > \bar{w}$, such that for any $\bar{w} < w_0 < w_2$, there exists $\bar{p}_h > 0$, so that $\nabla N^*_h(p_h) = 0$ and $\nabla \lambda^*_h(p_h) = 0$ for $\forall p_h \in (0, \bar{p}_h)$.

The proof of Theorem 2 can be found in Appendix C. Theorem 2 states that there exists a regime under which both the number of TNC drivers and the passenger arrival rates are unaffected by the congestion surcharge. This indicates that the ride fare, driver wage and passenger cost remain constant in the same regime and the surcharge incurs a direct money transfer from the platform to the city.
6. Comparison between Two Schemes of Congestion Surcharge

This section compares the trip-based congestion surcharge and the time-based congestion surcharge. To ensure a fair comparison, we first set a target for the city’s tax revenue. This target can be achieved by setting appropriate surcharge levels. For each surcharge scheme, we find the corresponding surcharge levels that exactly attain the targeted tax revenue and compare the two schemes under the same target. The model parameters are consistent with previous case studies in Section 4.2 and Section 5.1.

Figure 19-21 present the number of drivers, passenger arrival rate and the vehicle occupancy of the two surcharge schemes under different targets for the city’s tax revenue. Figure 22 and Figure 23 compare the ride fare and the pickup time for the two surcharge schemes, respectively. Figure 24 compares the platform profit under the trip-base congestion surcharge and the time-based congestion surcharge. These results reveal that under the same tax revenue, the time-based congestion surcharge offers a Pareto improvement as compared to trip-based surcharge (currently implemented in NYC). Under time-based congestion surcharge, more drivers are hired (Figure 19). Since the drive wage equals the minimum wage for both schemes (Figure 7 and Figure 16), this indicates a higher driver surplus under time-based congestion surcharge. For passengers, the time-based congestion surcharge leads to a lower ride fare but a longer waiting time. However, the time-based congestion surcharge also has higher passenger arrival rate (Figure 20). Since the demand function $F_p(c)$ is monotone, this indicates that the total travel cost $c$ is lower and the passenger surplus is higher under the time-based congestion surcharge. To summarize, the time-based congestion surcharge leads to higher driver surplus, higher passenger surplus, and higher platform profit (Figure 24), which benefits all participants of the transportation system. This is because the time-based congestion surcharge penalizes idle vehicle hours and motivates the TNC to improve the occupancy rate of the vehicles (see Figure 21). Based on the realistic data of San Francisco city, the surplus of increased vehicle occupancy will be distributed to all market participants, including the passengers, drivers, and the platform itself.

While the aforementioned results do not necessarily hold for all levels of targeted tax revenues, the conclusion is indeed applicable for a large range of model parameters in the regime of practical interest. To formally
present this general result, we define $N^*_t, w^*_t, \lambda^*_t, c^*_t, P^*_t, Tr^*_t$ as the optimal solution to (6) and denote $N^*_h, w^*_h, \lambda^*_h, c^*_h, P^*_h, Tr^*_h$ as the optimal solution to (12). They are respectively the optimal number of drivers, driver wage, passenger arrival rate, total travel cost, platform profit, the tax revenue of the city. Note that all variables with subscript $t$ depend on $p_t$ and $w_0$, and all variables with subscript $h$ depend on $p_h$ and $w_0$. We suppress this dependence to simplify the notation whenever it is clear from the context.

**Theorem 3.** Assume that the profit optimization problems (6) and (12) both have unique solutions. Assume that $F_p(c)$ and $F_d(w)$ satisfy the logit model as specified in (8) and (9), respectively. For any pickup time function $t_p$ that satisfies Assumption 1, any speed-density relation $v(N)$ that satisfies Assumption 2, and any model parameters $\Theta = \{\lambda_0, N_0, M, L, v_f, \kappa, \alpha, \epsilon, c_0, \sigma, w_0\}$, there exists $w_3 > \tilde{w}$, such that for any $\tilde{w} \leq w_0 \leq w_3$, there exists $\bar{p}_t$ so that for any trip-based congestion surcharge $p_t \in [0, \bar{p}_t]$, there exists a time-based congestion surcharge $p_h$ that offers a Pareto improvement, i.e.

$$N^*_h = N^*_t, w^*_h = w^*_t = w_0, \lambda^*_h > \lambda^*_t, c^*_h < c^*_t, P^*_h > P^*_t, Tr^*_h > Tr^*_t$$

The proof of Theorem 3 can be found in Appendix D. It shows that there exists a regime where time-based congestion surcharge offers a Pareto improvement compared to the trip-based one: in this regime, for any trip-based congestion surcharge, we can always find an appropriate time-based congestion surcharge where the same number of driver is hired, more passengers take TNC at a lower cost, the platform earns more profit, and the city collects more tax revenue to subsidize the public transit. For the case of San Francisco, we derive that $w_2 = \$28.95$/hour and $\bar{p}_t = \$3.89$/trip when $w_0 = \$26.35$/hour.

7. Conclusion

This paper studies the impact of two proposed congestion surcharges on TNC: (a) surcharge based on vehicle trips, and (b) surcharge based on vehicle hours. We used a market equilibrium model to assess the joint effect of minimum wage with either of these two congestion surcharges. Surprisingly, we find that neither congestion surcharge scheme can significantly affect the number of TNC vehicles since their effect are mitigated by the wage floor on TNC drivers. Furthermore, we showed that the time-based congestion surcharge offers a Pareto improvement as compared to the trip-based surcharge that is currently imposed in New York City. Under the time-based congestion surcharge, more drivers are hired, more passengers take TNC at a cheap overall travel cost, the platform earns a higher profit, and the city can collect more tax revenue from the TNC system to subsidize public transit. The proposed time-based congestion surcharge is simple to implement: the city periodically audit the operational data of the TNC platforms and collects the surcharge based on the accumulated vehicle hours during this period on each platform.

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Appendix

A: Calibrate Model Parameters

Here we describe the procedure to obtain model parameters for San Francisco. The parameters to be estimated include $\Theta = \{\lambda_0, N_0, M, L, v_f, \kappa, \alpha, \epsilon, c_0, \sigma, w_0\}$. We will obtain some of these parameters from validated sources, and estimate other parameter values based on inverse optimization.

The number of TNC rides and TNC drivers can be obtained from the SFCTA report [3]. It provides the trajectories of passenger arrival rates and the number of TNC vehicles over an entire day. We take a typically Wednesday and calculate that the average passenger arrival rate is $\lambda^* = 141.7/\text{min}$ and the average number of TNC vehicles is $N^* = 2800$ (Figure 1 of [3]). Based on [3], TNC contributes to approximately 15% intra-SF vehicles trips. This indicates that the arrival rate of potential passengers is $\lambda_0 = \lambda^*/0.15 = 944/\text{min}$.

Assume that 30% of the for-hire vehicle drivers work for TNC (the rest work for food delivery, package delivery, etc), then the total number of potential drivers is $N_0 = N^*/0.3 = 10000$.

The average TNC trip distance in San Francisco is 2.6 miles (Table 4 of [3]), and the average arterial traffic speed of San Francisco is around 14 mph [4]. This indicates that the average trip time is $t_0 = 11.14/\text{min}$. Based on the pricing formula of Lyft for San Francisco [39], a 2.6 mile and 11.14 minutes Lyft ride costs $14.2 if the surge multiplier is 1.2, i.e., $p_f^* = 14.2$. This total price consists of a service fee of $2.70, a base fare of $2.24, a per-mile fare of $0.93 and a per-minute fare of $0.40 [39]. The TNC platform keeps 100% of the service fee and 25% of the rest, leading to an average of 40% commission rate. This indicates that the driver wage is $w^* = \lambda^* p_f^* 0.6/N^* = $25.86/hour, since 60% of the total passenger fare is shared by all the $N^*$ drivers.

Given that the average pickup time is 5 minutes (Page 2 of [40]), we can obtain $M$ based on (10):

$$M = vt_F \sqrt{(N - \lambda/\mu)} = 40.8.$$  

where $\mu = 1/t_0$ is the service rate. To estimate $v_f$ and $\kappa$ in the Greenshield’s model, we need two data points along this linear curve (11). One data point is already available: we know that when $N^* = 2800$, the traffic speed is $v^* = 14$ mph. Another data point can be estimated by the fact that arterial traffic speed declined from 19 mph to 14 mph between 2009 and 2017, and it is estimated that TNC vehicles contributes to 55% of this decline [4]. This implies that without TNC vehicles, the traffic speed in 2017 would have

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been 16.8 mph, which provides another data point (when \( N = 0 \), traffic speed is \( v = 16.8 \)). We plug in these two points to obtain \( v_f = 16.8 \) mph and \( \kappa = 0.001 \).

Empirical study suggests that the value of travel time (VOT) ranges between $20 - $100/hour [41], and that the value of time while waiting for vehicle pickup is about 3 times to VOT [42]. If we take VOT at $60/hour, then the per-minute VOT is $1, and we have \( \alpha = 3 \).

The parameters of the logit model \((\epsilon, c_0, \sigma \text{ and } w_0)\) can be uniquely determined by the aforementioned parameter values based on inverse optimization. Here we set \( \epsilon, c_0, \sigma \text{ and } w_0 \) so that the optimal solution to the following unregulated profit maximization problem is consistent with the pre-set parameter values of \( \lambda_0, N_0, M, L, v_f, \kappa, \alpha \):

\[
\max_{p_f, p_d} \lambda(p_f - p_d) \tag{14}
\]

\[
\begin{align*}
\lambda &= \lambda_0 F_p(\alpha t_p(N - \lambda/\mu, v) + p_f) \\
N &= N_0 F_d \left( \frac{\lambda p_d}{N} \right) \tag{15a}
\end{align*}
\]

Inverse optimization yields \( \epsilon = 0.26 \), \( c_0 = 22.6 \), \( \sigma = 0.12 \), and \( w_0 = 33.57/\text{hour} \).

**B: Proof of Theorem 1**

First, we note that the unregualted problem (14) is equivalent to the following problem:

\[
\max_{p_f, N} \lambda p_f - Nw \tag{16}
\]

\[
\begin{align*}
\lambda &= \lambda_0 F_p(\alpha t_p(N - \lambda/\mu, v) + p_f) \\
N &= N_0 F_d(w) \tag{17a}
\end{align*}
\]

where we apply the definition of driver wage (4) and obtain an optimization problem over ride fare \( p_f \) and driver wage \( w \). We denote \( \tilde{N} \) and \( \tilde{p}_f \) as the optimal solution to this unregulated problem (14), and let \( \tilde{\lambda} \) and \( \tilde{w} \) be the corresponding optimal passenger arrival rate and driver wage.

When the minimum wage is greater than the optimal wage \( \tilde{w} \), i.e., \( w_0 > \tilde{w} \), the minimum wage constraint (7c) is active. In this case, the regulated profit maximization problem (6) can be reformulated as:

\[
\max_{p_f, N} \lambda p_f - Nw_0 \tag{18}
\]

\[
\begin{align*}
\lambda &= \lambda_0 F_p(\alpha t_p(N - \lambda/\mu, v) + p_f + p_t) \\
N &\leq N_0 F_d(w_0) \tag{19a}
\end{align*}
\]

where \( w_0 \) is given exogenously\(^3\). Note that (18) can be be equivalently viewed as nested maximization , where in the outer loop the platform chooses the number of drivers and in the inner loop the platform chooses the ride fare \( p_f \) to maximize the profit. To prove Theorem 1, let’s first consider the inner problem where \( N \) and \( w_0 \) is given and the platform solves:

\[
\max_{p_f} \lambda p_f \tag{20}
\]

\[
\text{s.t. } \lambda = \lambda_0 F_p(\alpha t_p(N - \lambda/\mu, v) + p_f + p_t) \tag{21}
\]

\(^3\)Compared to (17b), the supply function (19b) is inequality since \( w \) is endogenous in (16) while \( w_0 \) is exogenous in (18).
Denote the optimal value of (20) as \( \Gamma(N, p_t) \), which depends on \( N \) and \( p_t \). Since (6) has a unique solution and \( F_d \) and \( F_p \) are continuously differentiable, \( \Gamma(N, p_t) \) is a continuous function with respect to both \( N \) and \( p_t \). The regulated profit maximization problem (18) can be written as

\[
\max_N \Gamma(N, p_t) - Nw_0 \\
\text{s.t. } N \leq N_0 F_d(w_0)
\]

Similarly, the unregulated problem (16) can be written as:

\[
\max_N \Gamma(N, 0) - Nw \\
\text{s.t. } N = N_0 F_d(w)
\]

Since the solution to (24) is \( \tilde{w} \), when the minimum wage \( w_0 = \tilde{w} \), the optimal number of drivers for (22) and (24) are the same. Furthermore, based on (25), we have \( w = \frac{F_d^{-1}\left(\frac{N}{N_0}\right)}{F_d(w)} \). Therefore, (24) can be written as

\[
\max_N \Gamma(N, 0) - N F_d^{-1}\left(\frac{N}{N_0}\right) \\
\text{s.t. } N = N_0 F_d(w)
\]

The first order condition of (26) indicates that

\[
\frac{\partial^+ \Gamma(\tilde{N}, 0)}{\partial N} - \tilde{w} - \frac{\tilde{N}}{f_d(\tilde{w})} = 0,
\]

where \( f_d(w) = \frac{\partial F_d(w)}{\partial w} \). Since \( F_d(w) \) is strictly increasing, we have \( f_d(w) > 0 \), and thus we have

\[
\frac{\partial^+ \Gamma(\tilde{N}, 0)}{\partial N} - \tilde{w} = \frac{\tilde{N}}{f_d(\tilde{w})} > 0.
\]

We apply (28) to the regulated case (22) and derive that when the minimum wage satisfies \( w_0 = \tilde{w} \) and the congestion surcharge is zero, i.e., \( p_f = 0 \), the right derivative of the objective function (22) with respect to \( N \) is strictly positive (see equation (28)). Since the first order conditions are continuous with respect to \( w_0 \), there exists \( w_1 > \tilde{w} \) such that for \( \forall w_0 \in [\tilde{w}, w_1) \) we have

\[
\frac{\partial^+ \Gamma(N^*_t, 0)}{\partial N} - w_0 > 0,
\]

where \( N^* \) denotes the corresponding optimal solution for the regulated problem. Furthermore, due to continuity, for each \( w_0 \in [\tilde{w}, w_1) \), there exists \( \tilde{p}_t > 0 \) so that for \( \forall p_t \in [0, \tilde{p}_t > 0) \)

\[
\frac{\partial^+ \Gamma(N^*_t, p_t)}{\partial N} - w_0 > 0.
\]

This indicates that for \( \forall w_0 \in [\tilde{w}, w_1) \), there exists \( w_1 > \tilde{w} \) such that for \( \forall w_0 \in [\tilde{w}, w_1) \), the derivative of the profit with respect to the number of drivers are strictly positive. This indicates that the platform will earn extra profit if it hires more drivers. Therefore, it is optimal for the platform to hire all drivers available in the market, which gives \( N^*_t = N_0 F_d(w_0) \). Clearly, the optimal number of drivers does not depends on \( p_t \) when \( w_0 \) is fixed. This completes the proof.
C: Proof of Theorem 2

We can first show that there exists \( w_2 > \tilde{w} \), such that for any \( \tilde{w} < w_0 < w_2 \), there exists \( \tilde{p}_h > 0 \), so that \( \nabla N_h^*(p_h) = 0 \) for \( \forall p_h \in (0, \tilde{p}_h) \). Therefore, we have \( N_h^*(p_h) = N_0 F_d(w_0) \) for \( \forall p_h \in (0, \tilde{p}_h) \). Given this, the optimal number of passengers will not be affected by \( p_h \) when \( p_h \in (0, \tilde{p}_h) \). This is because when we know that the optimal number of drivers satisfies \( N^* = N_0 F_d(w_0) \), the profit maximization problem (12) can be written as:

\[
\begin{align*}
\max_{p_f} \quad & \lambda p_f \\
\text{s.t.} \quad & \lambda = \lambda_0 F_p(\alpha t_p(N_0 F_d(w_0) - \lambda / \mu, v) + p_f)
\end{align*}
\]

(31)

(32)

It is clear that \( p_h \) does not affect the optimal solution to (31). This completes the proof.

D: Proof of Theorem 3

To prove Theorem 3, we first show that there exists \( w_3 > \tilde{w} \), such that for any \( \tilde{w} \leq w_0 \leq w_3 \), there is \( \tilde{p}_t \) so that for any trip-based congestion surcharge \( p_t \in [0, \tilde{p}_t] \), there exists a time-based congestion surcharge \( p_h \) that offers the same tax revenue, but leads to higher passenger surplus and higher platform profit, i.e.,

\[
N_h^* = N_t^*, w_h^* = w_t^* = w_0, \lambda_h^* > \lambda_t^*, c_h^* < c_t^*, P_h^* > P_t^*, Tr_h^* = Tr_t^*
\]

The result of Theorem 3 then follows by slightly increasing \( p_h \) to make sure \( Tr_h^* > Tr_t^* \) without changing the sign of other inequalities. Such \( p_h \) exists due to continuity.

Based on Theorem 1 and Theorem 2, there exists \( w_3 > \tilde{w} \) such that for \( \forall w \in [\tilde{w}, w_3] \), there is \( \tilde{p}_t > 0 \) and \( \tilde{p}_h > 0 \) so that for \( \forall p_t \in [0, \tilde{p}_t] \) and \( \forall p_h \in [0, \tilde{p}_h] \), we have \( N_h^*(p_h) = N_t^*(p_t) = N_0 F_d(w_0) \). For notation convenience, we define \( \hat{N}(w_0) = N_0 F_d(w_0) \) and suppress the dependence on \( w_0 \) to simplify the notation whenever the context is clear. Since \( w_0 \geq \tilde{w} \), the minimum wage constraint are active in both (6) and (12), thus \( w_t^* = w_h^* = w_0 \).

To show that \( \lambda_h^* > \lambda_t^* \), we first note that since \( N_t^* = \hat{N} \), it is clear that \( \lambda_t^* \) is the optimal solution to:

\[
\begin{align*}
\max_{p_f} \quad & \lambda p_f \\
\text{s.t.} \quad & \lambda = \lambda_0 F_p(\alpha t_p(\hat{N} - \lambda / \mu, v) + p_f + p_t)
\end{align*}
\]

(33)

(34)

We can regard this as an optimization problem over \( \lambda \). After writing the objective function as solely a function \( \lambda \), the first order condition indicates that:

\[
F_p^{-1} \left( \frac{\lambda^*}{\lambda_0} \right) - \alpha t_p \left( \hat{N} - \frac{\lambda_t^*}{\mu}, v \right) + \frac{\lambda^*}{\lambda_0 f_p} \frac{1}{\mu} \frac{\partial}{\partial N_t} \left( \hat{N} - \frac{\lambda_t^*}{\mu}, v \right) - p_t = 0.
\]

(35)

Similarly, since \( N_h^* = \hat{N} \), we know that \( \lambda_h^* \) is the optimal solution to:

\[
\begin{align*}
\max_{p_f} \quad & \lambda p_f \\
\text{s.t.} \quad & \lambda = \lambda_0 F_p(\alpha t_p(\hat{N} - \lambda / \mu, v) + p_f)
\end{align*}
\]

(36)

(37)

\[\text{The proof is similar to that of Theorem 1, and is therefore omitted.}\]
The first order condition with respect to $\lambda$ gives:

$$
F_p^{-1}\left(\frac{\lambda^*_h}{\lambda_0}\right) - \alpha t_p\left(\tilde{N} - \lambda^*_h/\mu, v\right) + \frac{\lambda^*_h}{\lambda_0 f_p\left(F_p^{-1}\left(\frac{\lambda^*_h}{\lambda_0}\right)\right)} + \frac{\lambda^*_h \alpha \partial t_p(\tilde{N} - \lambda^*_h/\mu, v)}{\partial N_I} = 0. \tag{38}
$$

It can be verified that when $F_p(c)$ and $F_d(w)$ satisfy the logit model as specified in (8) and (9) and when Assumption 1 and Assumption 2 hold, each term of (35) and (38) is an increasing function of $\lambda$. By comparing (35) and (38)\(^5\), we have $\lambda^*_t < \lambda^*_h$. By strictly monotonicity, this indicates that $c^*_t > c^*_h$.

Last, we show that there exists $w_3 > \tilde{w}$, such that for any $\tilde{w} \leq w_0 \leq w_3$, there is $\tilde{p}_t$ so that for any trip-based congestion surcharge $p_t \in [0, \tilde{p}_t]$, there exists a time-based congestion surcharge $p_h$ which ensures $Tr^*_h = Tr^*_t$ and $P^*_h > P^*_t$. Note that $Tr^*_t = \lambda^*_t p^*_t$ and $Tr^*_h = N^*_h p^*_h$, and that there exists $\tilde{p}_t > 0$ so that for any $p^*_t \in [0, \tilde{p}_t]$, we can find $p^*_h$ such that $\lambda^*_t p^*_t = N^*_t p^*_h$. After setting $p^*_h$ and $p^*_t$ so that $Tr^*_t = Tr^*_h$, we apply a change of variable (i.e., $p_f = p_f + p_t$) to transform (6) into:

$$
\max_{p_f, p_d, N} \lambda(p_f - p_d) - \lambda p_t
$$

\begin{align*}
\lambda &= \lambda_0 F_p(\alpha t_p(N - \lambda/\mu, v) + p_f) \tag{40a} \\
N &\leq N_0 F_d\left(\frac{\lambda p_d}{N}\right) \tag{40b} \\
\frac{\lambda p_d}{N} &\geq w_0, \tag{40c}
\end{align*}

Then the two surcharge schemes (39) and (12) have the same constraints, and the optimal value to (39) satisfies:

$$
P^*_t = \lambda^*_t p^*_{f,t} - w_0 N^*_t - \lambda^*_t p_t \tag{41}$$

$$
P^*_h = \lambda^*_h p^*_{f,h} - w_0 N^*_h - N^*_h p_h \tag{43}$$

where $p^*_{f,t}$ is corresponding optimal ride fares for the trip-based congestion surcharge. The optimal value to (12) satisfies

$$
P^*_t = \lambda^*_t p^*_{f,t} - w_0 N^*_t - \lambda^*_t p_t \tag{42}$$

$$
P^*_h = \lambda^*_h p^*_{f,h} - w_0 N^*_h - N^*_h p_h \tag{44}$$

where $p^*_{f,h}$ is corresponding optimal ride fares for the time-based congestion surcharge.

Based on Theorem 2, we have $\lambda^*_h(p_h) = \lambda^*_h(p_h)$ and $N^*_h(p_h) = N^*_h(0) = \forall p_h \in [0, \tilde{p}_h)$. Therefore, $\lambda^*_h(p_h), N^*_h(p_h)$ and $p^*_{f,h}(p_h)$ are the optimal solutions to the profit maximization problem with minimum wage only (i.e., $w_0 > \tilde{w}$ and $p_h = 0$):

$$
\max_{p_f, N} \lambda p_f - N w_0 \tag{45}
$$

\begin{align*}
\lambda &= \lambda_0 F_p(\alpha t_p(N - \lambda/\mu, v) + p_f + p_t) \tag{46a} \\
N &\leq N_0 F_d(w_0) \tag{46b}
\end{align*}

This indicates that $\lambda^*_h p^*_{f,h} - w_0 N^*_h > \lambda^*_t p^*_{f,t} - w_0 N^*_t$\(^6\). This indicates that $P^*_h > P^*_t$, which completes the proof.

\(^{5}\mu \text{ and } v \text{ depend on the number of TNC vehicles } N. \text{ Since } N^*_h \text{ and } N^*_t \text{ are the same, we do not need to distinguish } \mu \text{ and } v \text{ for these two cases.}
\(^{6}\text{Otherwise, this contradicts with the fact that } \lambda^*_h, N^*_h, p^*_h \text{ as the optimal solution to (45).}