# PRICING TIME: MECHANISM FOR DESTINATION PREFERENCE IN RIDESHARING PLATFORMS

RICHARD XU

Abstract. In a ridesharing platform such as Uber, drivers may prefer trips that move toward a certain destination. This preference may come from personal reasons, such as a need to return home at a certain hour, or beliefs that certain areas have more customers. As such, some drivers have stronger preferences for destination over others. We argue that the current policies in ridesharing platforms inadequately address this driver heterogeneity. Then, we propose a mechanism that builds on the existing "Destination Filter" to address this variation. We show that the mechanism is strategy proof and produces additional revenue to both the ridesharing platform and increases driver utility, and answer practical concerns if the theory were to be adopted.

## 1. Introduction

A *ridesharing platform* such as Uber matches incoming ride requests with drivers with greater flexibility than traditional taxi systems [1].[1] A driver does not need to work for the platform full time, but can join the app when she is free and set her own hours with the platform. As a result, more people can work Uber driving into their schedule. This increases the supply of drivers and also boosts employment in the region. Currently, Uber connects customers to drivers in a three step process.

(1) The customer requests a ride toward a destination.
(2) The platform broadcasts the request to nearby drivers.
(3) A driver accepts the ride and picks up the customer.

---

*Date*: December 9th, 2019.

[1]For brevity, we will use Uber to refer to a general ridesharing platform.

By default, the driver does not know about the destination of the trip until she has picked up a customer. As a result, the driver has to operate with incomplete information in this process. Furthermore, the drivers are compelled not to cancel a trip because the service may negatively impact their work. Uber is generally secretive about their practices, and there are few reliable sources about how drivers can do well. However, drivers have reportedly received warnings that cancelling trips can lead to deactivation of their driver apps [11], and the general paranoia is already an issue. Not having information about a trip's destination is especially challenging when the driver has a certain direction in mind.

**Example 1.** Suppose it's 4:30 pm and the Uber driver is a mother who needs to return home and cook for her children. She takes on another trip, and it is 1 hour in the opposite direction of her house. Fearing that her account will be deactivated if she cancel, she takes the trip and stroll through heavy traffic on the way back, and returns by 7pm. In Economic terms, the driver values income and time arriving at home, and currently her expected utility change from taking a trip is negative. As a result, she is likely to close the Uber app in the future and forego the extra income. This is known as "deadheading" in practice.

The example above highlights how withholding information from the driver can decrease their welfare. The risk of taking a trip in the opposite direction makes some drivers unwilling to accept new rides and decrease the supply of the market.

A growing literature has studied how to structure prices in ridesharing platforms to account for variations in supply and demand [3][6]. However, these papers mostly consider variations across space and time and focuses on "surge pricing" used by the platforms. They ignore the heterogeneity within the drivers. Given that many Uber drivers only drive part time, there is larger variance within the Uber drivers than in traditional taxi services. As a result, the past work fail to address the inefficiency that comes from Uber ignoring driver preferences.

1.1. **Attempts to Remedy.** Uber has recognized that this issue and introduced the "destination filter", where drivers can set a driver destination and Uber attempts to match the driver with trips going in that direction [9]. While this is a strong first step to address driver heterogeneity, it runs into issues about incentive.

A driver with a weak preference for a direction, perhaps anticipating increased traffic or longer rides in certain areas, may also use this feature. As long as the demand for rides is high enough, the utility lost from potentially longer wait time is smaller than the utility gained from using the feature. Contrast this with the driver in example 1, who has a strong preference in direction because of her personal schedule. The latter group cannot signal her strong preference, and Uber is forced to treat the two groups the same. Since everyone seem to have a directional preference, the feature decreases the supply of drivers. This type of herding behavior forces Uber to push trips that do not match any driver's preference to arbitrary drivers, defeating the original purpose of the feature. The pattern can be seen in the real world, where drivers begin to find the feature increasingly ineffective [10]. Uber has experimented with two strategies for fixing the situation.

- Limit the feature to two trips per day. This is common in most cities, but it does not resolve the incentive issue. Some full time drivers may have only weak destination preference throughout the day, and drivers with a strong destination preference may need more than two trips.
- Decrease the price paid to workers by 30% under this mode and redistribute the rest to drivers not using the feature. This is tested in four cities at the start of this year. While this may solve the incentive issue, the feature is limited and unexplained. As a result, it caused outrage among drivers who called the policy "Uber socialism" [8].

A market forced to impose rules on its traders is a sign of a market failure. Here, the issue is that drivers cannot signal their willingness to pay for a trip that is aligned with their destination. We will provide a mechanism that improves upon the destination filter system and show that it is strategy proof and improves driver welfare. Next, we measure the mechanism's impact on driver welfare through a simplified model of ridesharing platforms. Finally, we highlight practical concerns to consider if the mechanism is adapted in practice.

## 2. Pricing the Filter

The mechanism works as follows. First, the driver reports a destination filter and how much they are willing to pay for trips that move near that destination. For example, they may state that "I am willing to get paid 10% less than the usual time fare if the trip is in the direction of my destination". Then, the mechanism can calculate how much the driver is willing to pay per minute the trip gets her closer to the destination, which we denote $WTP$.

When a ride arrives, each driver client bids on behalf of their driver a premium $(\Delta T - T_{pickup}) \cdot WTP$ for that ride. $\Delta T$ measures how much closer the trip destination is to the driver's destination given their current position, and $T_{pickup}$ is the estimated time it takes to pick up the customer.

The ridesharing platform performs a second price auction and the bidder with the highest bid receives the trip first. The person receives a window to accept or decline the trip. If she accepts, the bidder pays a premium equal to the second bid (if no driver is around, she pays 0). We refer to the payment as *profit to the platform*, but who this payment goes to can depend on the platform's strategy – see section 4. If she declines, her bid is removed and the second place bidder pays the premium equal to the third bid. The option to accept or decline a trip is a classic Uber feature that should be kept, and a time such as 10 seconds before the trip is offered to the next bidder should be enough to make the wait time for the customer low enough.

**Example 2.** Suppose the driver at position $A$ states "I am willing to be paid 10% less than the usual fare if the trip is towards position $B$", the standard Uber fare for time is \$15 per hour, and a customer requests a ride from position $C$ to $D$. $C$ is 5 minutes from $A$, and $D$ is 10 minutes closer to the driver's goal $B$ than $A$ is. In practice, these values can be found with a navigation app such as Google Maps.

Then, Uber first calculates that the driver is willing to pay $\$15/h \cdot 10\% = \$0.025/\min$ for a trip completely towards their destination. For this trip, the driver needs to spend 5 minutes picking up the customer but gains 10 minutes because the destination of the trip is closer than the start destination. Then, the app will bid $5 \cdot \$0.025 = \$0.125$ on behalf of the driver.

**Theorem 1.** Suppose the drivers have constant marginal utility for small amounts of time, then the mechanism is strategy proof.

*Proof.* We use a result from mechanism design known as the *taxation principle*. The principle states that a mechanism is strategy proof if it has agent-independent pricing and is agent optimizing, and is first found by Desgupta et. al[5] and covered in [7].

Suppose a driver receives the trip given her reported WTP. Then, the price she pays is equal to the second largest bid. This is independent of her reported WTP, which ensures agent-independent pricing.

Next, suppose that the driver received the trip. By taking the trip, her value for the trip is at least $(\Delta T - T_{pickup}) \cdot WTP$ more than the standard fare. Since she chooses the drive, the agent is better off taking the trip at standard fare when she has no location preference. Thus, she is better off taking the assigned trip. Similarly, if a driver has not received a trip, then the premium she has to pay to receive that trip is higher than her value for the trip, and she is better off not driving. Therefore, in both cases the mechanism is agent optimizing.

**Note**. The proof is not completely formal, but the formality comes at a cost of a lot of notation. If this becomes a full paper I will flesh out the notations. □

Notice that nowhere in the proof did we directly invoke the assumption that drivers have constant marginal utility. Rather, the result is used to ensure that the mechanism is agent optimizing. Therefore, with an analogous proof we can show the following result.

**Corollary 2.** Suppose the driver can fully express her willingness to pay for time, then the mechanism is strategy proof.

However, be aware that the strategy proof condition holds only while Uber is willing to uphold the policy all the time, illustrated by the following example. For example, that includes not pushing a trip on a driver who bids negative value for a trip. Otherwise, the mechanism becomes no longer agent-optimizing and some drivers may opt back to turning off their app.

It is difficult to resolve this issue. For example, if Uber decides to subsidize drivers when all drivers bid negative values, then a driver can collude by opening a customer account, requesting trips in opposite direction of the destination filter while no driver is around, and profitting from the subsidy. Since customer wait time and high matching rate is important to Uber, this is a lacking feature of the policy that should be resolved.

**Note.** As the research continues, this section would be expanded to include other properties of the mechanism. As far as I am aware, the mechanism is also efficient, individually rational and has no deficit. The proofs mostly follow from the construction of the mechanism, but I am unsure whether it adds much to the paper. There are likely properties that are more relevant to the mechanism, which I will find with further research or a course on mechanism design.

## 3. Revenue Performance

We assume drivers live on a 2-dimensional grid with the Euclidean metric. That is, the time to travel between two points is equal to the straight-line distance between them. A trip has a base cost $C$ and takes time $T$ to complete. Drivers are distributed uniformly at random on the map with density $\rho$. Among the drivers, with probability $p$ a driver has a strong preference in some direction $\theta \sim \mathrm{Unif}(0, 2\pi)$ with a WTP of 1. That is, for every distance 1 travelled in the direction given by $\theta$, the person is willing to forego \$1 of the profit. The rest of the drivers have a preference in the $+x$ direction with a WTP of $\epsilon$. The drivers with a low WTP provide a guarantee that each region likely includes some driver with a low WTP and thus most trips are fulfilled.

**Theorem 3.** Let $c = p\rho\pi r^2/2$. f each trip connects the driver to nearby $r$ drivers and $r$ is smaller than the length of the trip, then on average, each trip gives at least $\frac{\sqrt{2}}{2}(1-e^{-c})T$ additional revenue to the platform and expected increase in utility of at least $\frac{\sqrt{2}c}{2}e^{-c}T$.

**Note:** This theorem can be extended to drop most of its assumptions, and it comes down to having more time and modeling experience. The proof is mostly techniques with probability, which can be found in [4].

*Proof.* Since the drivers are distributed uniformly on the map, the number of drivers in a $r$ radius of the trip requester with a strong preference is distributed as $\text{Pois}(p\rho\pi r^2)$. For a driver, let $\Delta\theta$ be the difference between her preferred direction and the direction of the trip. By the Euclidean metric, this driver has value $\cos(\Delta\theta)T$ for the trip.

Since their preference direction $\theta \sim \text{Unif}(0, 2\pi)$, we get $\Delta\theta \sim \text{Unif}(0, 2\pi)$ as well. Then, $\Pr(\cos(\theta) > 0) = \frac{1}{2}$. By the splitting properties of the Poisson distribution, the number of drivers with preference direction aligned with the driver is $N \sim \text{Pois}(p\rho\pi r^2/2) = \text{Pois}(c)$.

Let $X$ be the value to the driver and $Y$ be the additional revenue received by the platform. For each driver with a positive value, let $V_1, \ldots, V_N$ be their value for the trip and $\theta_i$ be the difference between their direction. Since the mechanism is strategy proof, $b_i = V_i$. Since $V_i > 0$ for all the drivers and $\cos(\Delta\theta_i) = \cos(2\pi - \Delta\theta_i)$, assume WLOG that $\theta < \frac{\pi}{2}$. Then, the driver with the highest value is the driver with the smallest $\Delta\theta$, which also makes intuitive sense.

Using the representation for the order statistics of a uniform [4], $\min \Delta\theta_i \sim \frac{S}{T}$ where $S \sim$ Expo and $T \sim \text{Gamma}(N+1)$. Taking the expected value, $E(\min \Delta\theta_i) = \frac{\pi}{2(N+1)}$. Next, $\cos(-\theta)$ is increasing and concave when $\theta \in [0, \pi/2]$. Then, by Jensen's inequality, $E[\max \cos(\Delta\theta_i)] \geq \cos(E(\min \Delta\theta_i)) = \cos \frac{\pi}{2(N+1)}$. Similarly, we find the expected value of the second bid is $\cos \frac{\pi}{N+1}$.

Since $N \sim \text{Pois}(c), \Pr(N \geq 1) = e^{-c}$. Since the revenue to the platform is nonnegative, we get that the expected revenue to the platform is at least $e^{-c} \cdot \cos \frac{\pi}{2 \cdot 2} = \frac{\sqrt{2}}{2} e^{-c}T$.

Since $\Pr(N = 1) = e^{-c}$ and the increase in utility to the driver is nonnegative, we get the utility increase is at least $ce^{-c}\cos(\frac{\pi}{4})T = \frac{\sqrt{2}c}{2}e^{-c}T$. □

Notice that the revenue for the platform is higher when the supply of drivers is higher, while the increased utility for the driver is lower in that case, which makes sense since there is more competition. The value of $r$ is decided by the platform, and while a larger value of $r$ increases the platform's profit, the cost of a far-away driver to pick up the customer can outweigh the benefits.

**Note.** Currently the model makes many assumptions, but this is the best I can do with a purely theoretical model and my current knowledge. A simulation with real world traffic data will likely help, and if the project is fleshed out it would go here.

## 4. Practical Considerations

**User Interface to query WTP.** A good user interface will help drivers understand what the new destination filter does. The concept of "Willingness to Pay" may not be easy to grasp for a driver, and a driver may not be aware of her own willingness to pay for time. While driving Uber is a repeated game and drivers may learn their evaluations after multiple trips, a good user interface can help people learn the feature and use it quickly.

**Where should the revenue go?** By default, consumers pay the full price of the rides while the drivers get paid reduced fare determined by the auction. Then, there is a price difference and it is unclear who the profit should go to. The answer to this question will depend on the kind of company Uber is aiming for. If Uber aims to be a platform matching drivers to consumers, then the price difference would go to the consumer. However, if Uber is more like a taxi company with contractors that provide rides, then they might pocket the revenue or spend it on employee welfare.

**Uber Publicity.** Uber continues to have a publicity problem regarding their treatment towards drivers and secretive policies [2]. As a result, drivers are unlikely to trust the policy change when it releases. Even though the policy expands a driver's choice set and can help them earn additional income when they have a set destination in mind, on a first glance the policy may seem like Uber trying to further take money away from the drivers. As such, the policy change should be given a positive name and should try to be as transparent as possible.

## 5. Further Research

**Actual distribution of WTP.** Constant marginal utility for time may not be a good model. Rather, the utility changes may come in steps. For example, a driver picking up her children from school may be roughly indifferent between arriving ten minutes late or on time, but prefers to be on time over outcomes when she is late. We aim to do research on how to best model people's marginal utility for time. If the utility function looks more like a step function, then it can be beneficial to change the type of user interface to reflect this. For example, a fill in the blank interface that states "I need to go to insert destination by insert time" may better reflect some driver's needs.

**Better modeling for revenue.** The current model that computes the expected revenue for the platform and utility for driver is quite limited. In particular, real cities are not shaped like a flat grid with Euclidean distance, and driver destinations are specific locations, not directions. We aim to perform a simulation of the policy on cities with real world traffic data and Uber platform data. This will require coordination with Uber to perform, but can be invaluable for ridesharing platform research.

**Additional Collaboration with Uber.** In addition to getting real world traffic data to work with, the next step would be to implement the feature after its finer details have been ironed out. Some A/B testing and canary testing would be necessary since the policy can have a large effect on the market. Since the policy requires driver interactions, it would also help to have Uber drivers test the policy and perform post-studies interviews and surveys.

**Continue to expand rideshare research.** The current research body of rideshare research is primarily focused on the surge pricing feature. While this is an important feature of ridesharing platforms, these platform contain many more policies and pricing strategies than surge pricing. Furthermore, these current research focus on ,

## 6. Conclusion

In this paper, we have identified how current ridesharing platforms inadequately address driver heterogeneity when it comes to drivers' destination preferences. We examine past policies aimed to address the issue by examining how they line up with driver incentives. Then, we propose a mechanism and show that it is strategy proof and can generate additional revenue for the platform through a model. Finally, we offer practical suggestions for the policy if it were to be implemented and explore future directions for this pseudo-paper. The policy we proposed still require additional fine tuning, but it already aligns incentives in a way that the current policy cannot.

## 7. Final Thoughts

Dear Scott and Ravi, thanks again for the fun course. I now believe that I can be a market designer and change the world. Hope you enjoyed reading my proposal. I decided to make it into a pseudo-paper and put my closing thoughts here.

I generally found it difficult to relate my research in ridesharing back to existing papers. While discussing my research with David Parkes, he mentioned that the field is difficult because it is unclear how to break down the problem of "how to improve rideshare" into policy suggestions that can be adequately explained with Economics. Perhaps because the field is difficult to tackle and ridesharing platforms are generally new, the field is at a stage where we still don't know which tools are effective. As a result, I found that papers give suggestions that all may help, but without a clear direction. It is unclear to me what the space is missing, but I will keep exploring.

The paper combined many areas of my studies this semester. The strategy-proofness proof and general mechanism design background come from CS 136. The modeling techniques is inspired by Econ 1011. Finally, knowledge about how to work with distributions come from Stat 210, and that helped make the model interesting and tractable. The integration of multiple fields of study made this project especially interesting to do, but I think it can also be a sign that I do not have all the relevant knowledge to tackle it. If everything I study seems to apply, perhaps the most appropriate tools are subjects I am yet to study. If I were to continue with the project, having a co-author who is experienced with economic theory can be very beneficial.

I want to find some distance away from the project because it has somewhat consumed me over the past couple of weeks. The winter break will be a good time to reset myself. While the "future work" section are often used in papers to pad out the story and give optimistic promises (often with limited application), I believe the directions I left in the section are highly important for this project. Here is the breakdown of the items' importance in my mind.

- Interviews with Uber drivers and past papers about how we value time will nail down the willingness-to-pay part of the model,
- Doing more economics will make the modeling more solid in general.
- Whether or not Uber experiments with this policy suggestion can make or break the paper. Putting theory into practice is essential in Market Design. In this case, there are many externalities that the model does not quantify. Having actual data from a test run of the policy will give the paper much more awesome. However, convincing Uber to do an experiment requires effort, the first of which is thinking about the proposal more to make sure it is solid.

I hope you enjoyed the paper. I see a lot of work for this project and enjoyed working through it. Still can't believe that I walked into the course knowing no Economics – guess a semester with triple Economics courses is quite effective. Enjoy your winter break, and best wishes to your family.

Sincerely,

Richard

## References


[1] Joshua D Angrist, Sydnee Caldwell, and Jonathan V Hall. Uber vs. taxi: A driver's eye view. Technical report, National Bureau of Economic Research, 2017.

[2] The Atlantic. A field guide to the company's ongoing pr nightmare. `https://www.theatlantic.com/technology/archive/2017/04/ubers-pr-nightmare-a-field-guide/523269/`. Accessed 2019-12-10.

[3] Siddhartha Banerjee, Ramesh Johari, and Carlos Riquelme. Pricing in ride-sharing platforms: A queueing-theoretic approach. In *Proceedings of the Sixteenth ACM Conference on Economics and Computation*, pages 639–639. ACM, 2015.

[4] Joe Blitzstein and Carl Morris. *Probability for Statistical Science*. Cambridge University Press, forthcoming.

[5] Partha Dasgupta, Peter Hammond, and Eric Maskin. The implementation of social choice rules: Some general results on incentive compatibility. *The Review of Economic Studies*, 46(2):185–216, 1979.

[6] Hongyao Ma, Fei Fang, and David C Parkes. Spatio-temporal pricing for ridesharing platforms. *arXiv preprint arXiv:1801.04015*, 2018.

[7] David Parkes and Sven Seuken. *Economics and Computation*. Cambridge University Press, forthcoming.

[8] RideGuru. Uber destination mode paying 30% less. `https://ride.guru/lounge/p/uber-destination-mode-paying-30-less`. Accessed 2019-12-09.

[9] Uber. Set a driver destination. `https://help.uber.com/partners/article/set-a-driver-destination?nodeId=f3df375b-5bd4-4460-a5e9-afd84ba439b9`, 2019. Accessed 2019-12-09.

[10] UberPeople. Destination filter. `https://uberpeople.net/threads/destination-filter.358925/`. Accessed 2019-12-09.

[11] UberPeople. Acceptance and cancellation rate. `https://uberpeople.net/threads/acceptance-and-cancellation-rate.249711/`, 2018. Accessed 2019-12-09.