Lyft in Toledo, OH Case Study by Vivek Saravanan

Table of Contents

Snapshot of the Future

Future Lyft Riders

> "Lyft never fails to impress me with their reliable service. I can always count on finding a ride from the airport to downtown Toledo!”

> "Thank you, Lyft, for always being there to whisk me away from the airport to the heart of

Future Lyft Drivers

> "Being a Lyft driver on the airport-to-downtown Toledo route has been a game-changer for me. The increased demand and higher pay are incredibly satisfying.”

> Driving with Lyft on the route from the airport to downtown Toledo has been a dream. The steady stream of passengers and

> Toledo. Your availability is unbeatable!”

> improved earnings make me so happy!”

Main Takeaways (tl;dr)

- Optimal driver wage set at $21, correlating with a $4 fee for Lyft and an 82% match rate.
- Launch plan includes implementing the $21 rate for 80% of rides, conducting pricing experiments for the remaining 20% in the first quarter, and adjusting strategies based on the results.
- Introduce a driver bonus of $100 for completing 150 rides to incentivize and reward drivers. The plan will be adaptable throughout the year, considering seasonal patterns and annual events in the Toledo area.

Context

In this case study, I am assuming the position of a Pricing Product Manager at Lyft, tasked with determining the pricing framework for Lyft's operations in the emerging market of Toledo, Ohio. Specifically, my attention is centered on a single route: transportation to and from the airport to downtown Toledo.

Some quick facts about Toledo!

Population	**Location**	**Nickname**	**Sports**	**Industry**
268,501 (2021)	northwest Ohio	Glass City	Toledo Mud Hens	Manufacturing , healthcare, etc.

The following table provides an overview of the available information regarding Lyft's presence in Toledo.

Total Fee	$25
Lyft’s Cut	$6
Driver Wage	$19
Match Rate (@ $6)	60%

Match Rate (@ $3)	93%
Rides Requested per User per Month	1
Rides Completed per Driver per Month	100
Rider Churn Rate (Match)	10%
Rider Churn Rate (No Match)	33%
Rider CAC	$10 - $20
Driver Churn Rate	5%
Driver CAC	$400 - $600

Another constraint: the fixed rider fee of $25 cannot be altered.

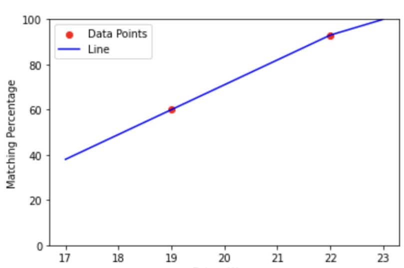
My primary goal is to maximize net revenue in the upcoming 12 months. Additionally, since this is a new market, I must also focus on establishing Lyft's reputation and popularity among both riders and drivers- happy customers → happy company!

Analysis

Exploration and Discovery

Given that the customer fee remains fixed at $25, the adjustable aspect within the equation is the driver wage, which directly influences Lyft's earnings per ride (Lyft's cut). This variable has far-reaching consequences, impacting various factors such as the matching rate of rides, which, in turn, indirectly affects rider churn and customer acquisition costs. With this understanding, I proceeded while keeping these factors in mind.

To initiate my analysis, I began by projecting the provided matching percentages and driver wages. For the sake of simplicity, I assumed linear correlation. However, this may not be the case, and I would need to validate this assumption with real data.



Driver Wage	17.0	18.0	19.0	20.0	21.0	22.0	23.0
Matching Percentage	38.0	49.0	60.0	71.0	82.0	93.0	100.0

Note: Based on the plot and table above, beyond approximately $23, the matching rate exceeds 100%. This implies an excess supply of drivers in that price range.

Next, I calculated four essential metrics to assist in determining the optimal price point that would result in the highest net revenue. These metrics include

- Weighted Churn Rate
- Average Revenue per User
- Monthly Customer Lifetime Value
- Annual Customer Lifetime Value

These calculations incorporated Lyft's Cut, the Matching Percentage, and the two Rider Churn Rates. The Customer Lifetime Value (CLV) metrics provide valuable insights into the revenue expected from each customer over their lifetime. These metrics are highly correlated with net revenue and help in understanding the long-term revenue potential.

	Driver Wage	Matching Percentage	Churn Rate	Lyft Cut	ARPU	Customer Lifetime Value	Annual CLV
0	17.0	38.0	24.26	8.0	3.04	12.53	12.08
1	18.0	49.0	21.73	7.0	3.43	15.78	14.95
2	19.0	60.0	19.20	6.0	3.60	18.75	17.30
3	20.0	71.0	16.67	5.0	3.55	21.30	18.91
4	21.0	82.0	14.14	4.0	3.28	23.20	19.47
5	22.0	93.0	11.61	3.0	2.79	24.03	18.57
6	23.0	100.0	10.00	2.0	2.00	20.00	14.35

Based on the table above:

- Driver wage of $22 yields the highest Monthly CLV
- Driver wage of $21 results in the highest Annual CLV

Considering our scope is over a year, the Annual CLV becomes the decisive factor, leading us to select a driver wage of **$21**. However, it's important to note that the analysis thus far has been based on discrete numbers, without considering continuous values. Consequently, I conducted a revised analysis by incorporating 10,000 data points ranging between $17 and $23. This revealed that the highest Annual CLV of $19.48 corresponds to a driver wage of **$20.94**. In the next step, I will incorporate this selected price point into a year-long simulation to evaluate its actual impact on generating the highest net revenue.

Simulation and Validation

I designed a simulation that accounted for churn, as well as rider and driver growth, in order to calculate the net revenue.

Assumptions:

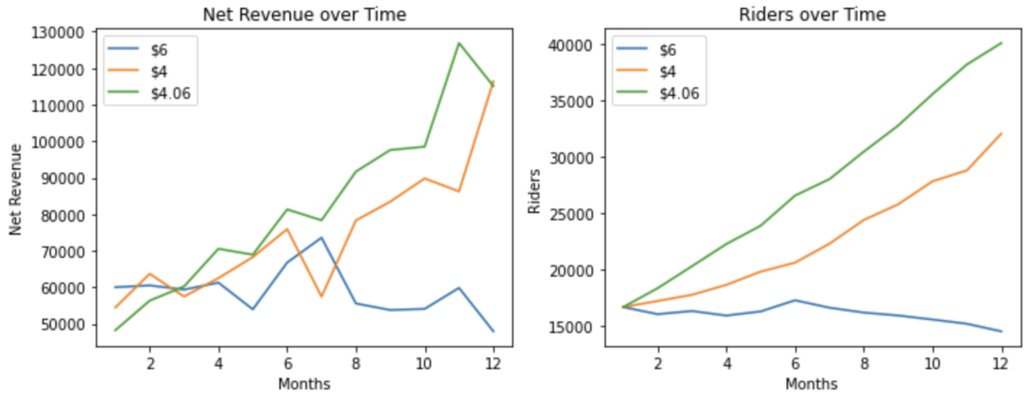
1. Initial Driver and Rider Numbers: Assuming that drivers complete 100 rides per month and riders request an average of 1 ride per month, with a 60% matching rate, I determined the starting number of 16,667 riders and 100 drivers. This number was derived from the fact that 100 rides per driver would account for roughly 60% of the number of riders.
2. Rider and Driver Monthly Growth: Each month, the number of riders experiences a growth rate of 15% to 25%, while the number of drivers grows by 5% to 10% before accounting for churn. These growth percentages were chosen arbitrarily.
3. Randomness: To replicate real-world scenarios where precise numbers are rare, the ride requests, matches, and percentages of rider and driver growth incorporate some level of randomness.

These assumptions were made to simulate a dynamic environment that reflects the inherent variability found in real-world conditions. I then conducted three separate iterations of the simulation, each using a distinct price point.

- Lyft’s Cut of $6 (Driver Wage of $19)
- Lyft’s Cut of $4 (Driver Wage of $21)
- Lyft’s Cut of $4.06 (Driver Wage of $20.94)

	Month	Riders	Drivers	Rides Requested	Rides Completed	Churned Riders	Churned Drivers	New Riders	New Drivers	Rider Growth %	Driver Growth %	Total Revenue	Driver Wages	Net Revenue
0	1	16667	100	14515	11874	2058	5	3732	8	22.39	8.64	296850	248641.56	48208.44
1	2	18341	103	16964	13873	2407	5	4362	6	23.79	5.90	346825	290500.62	56324.38
2	3	20296	104	18192	14830	2592	5	4561	9	22.48	9.32	370750	310540.20	60209.80
3	4	22265	108	21312	17371	3037	5	4665	7	20.96	7.04	434275	363748.74	70526.26
4	5	23893	110	20975	16971	3018	5	5693	10	23.83	9.48	424275	355372.74	68902.26
5	6	26568	115	24470	20025	3469	5	4925	8	18.54	7.55	500625	419323.50	81301.50
6	7	28024	118	23722	19294	3390	5	5830	11	20.81	9.90	482350	404016.36	78333.64
7	8	30464	124	27821	22575	3988	6	6302	11	20.69	9.06	564375	472720.50	91654.50
8	9	32778	129	29458	24032	4193	6	6989	7	21.32	6.04	600800	503230.08	97569.92
9	10	35574	130	29816	24255	4260	6	6888	12	19.36	9.79	606375	507899.70	98475.30
10	11	38202	136	38555	31247	5535	6	7438	12	19.47	8.84	781175	654312.18	126862.82
11	12	40105	142	34821	28341	4972	7	7493	9	18.68	6.77	708525	593460.54	115064.46

Note: the table above represents a simulation of Lyft’s Cut of $4.06 (Driver Wage of $20.94)



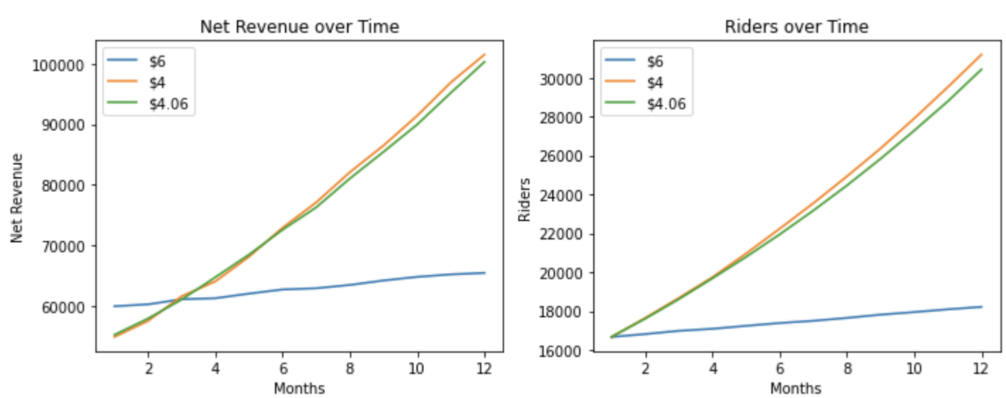
Net Revenue @6: $780,444

Net Revenue @4: $840,160

Net Revenue @4.06: **$903,719.46**

The above plot illustrates that my initial choice of a driver wage at $20.94 yielded the highest revenue! It generated approximately $100,000 more net revenue compared to our original driver wage of $21. Additionally, the graph indicates a notable increase in the overall number of riders. This surge can be attributed to higher match rates, which effectively reduced the churn rate among riders.

To account for potential variability in the simulation results, I performed an additional 1,000 iterations for each simulation and calculated the averages across all variables. The plots displayed below appear smoother as they represent the average values across the 1,000 trials. From these plots, it becomes evident that the difference in net revenue between the driver wage of $21 and $20.94 is relatively small, with the $21 wage being slightly favored.



Net Revenue @6: $754,137.89

Net Revenue @4: **$913,485.17**

Net Revenue @4.06: $913,071.38

Conclusion: Based on the simulations, opting for a higher driver wage would be the preferable choice for maximizing net revenue. Therefore, I would recommend a **final driver wage of $21**, as it consistently yielded the highest net revenue in the simulations.

Github Link

You can find the code I used for all my calculations and visualizations in this repository, accessible through the following link!

```
https://github.com/viveksaravanan/Lyft-Case-Study/
```

Implementation

Impact

By setting the driver wage at $21, Lyft would earn $4 per ride, with a ride matching percentage of 82%.

This represents a decrease of $2 per ride compared to the initial starting point. However, this pricing strategy makes sense as it not only leads to higher net revenue but also brings about positive effects crucial for Lyft's sustainability in Toledo.

1. **Decreased Rider Churn Rates:** Naturally, riders would experience more successful matches, resulting in a reduction in rider churn rates over time.
2. **Decreased Driver Churn Rates:** Although not directly measured in the simulation, it is reasonable to expect that when drivers are compensated at a higher rate, they are more likely to remain active on the platform, thereby reducing driver churn rates.
3. **Increased Platform Usage:** As a consequence of decreased churn rates, more users would be inclined to remain on the platform and would be more likely to recommend Lyft to others, leading to increased platform usage and potential growth. Consequently, the need for extensive spending on customer acquisition costs would be reduced.

Overall, this pricing strategy not only maximizes net revenue but also promotes improved user retention, driver satisfaction, and increased platform usage, all of which contribute to Lyft's long-term success and viability in Toledo.

Launch

Although my analysis identified an optimal driver wage of $21, I would not recommend fixing this price for the entire duration of the upcoming year. Instead, I propose the following strategy for the next quarter:

- 80% of rides: Maintain the driver wage at $21.
- 20% of rides: Conduct A/B testing or implement a reinforcement learning algorithm to experiment with different price points and evaluate their impact on the matching percentage.
- $100 bonus for drivers that complete 150 rides

The rationale behind conducting further testing for 20% of the rides is rooted in the assumption made during the analysis that there is a linear relationship between the driver wage and the matching percentage. By conducting these tests, I aim to validate this assumption. Throughout the quarter, I would track relevant metrics such as churn, matching percentage, and introduce new metrics to track such as review counts and ratings. At the end of the quarter, I would review the comprehensive information gathered and adjust the pricing strategy accordingly based on the findings.

The implementation of the bonus system can serve as a powerful incentive for drivers to accept more matches. By setting monthly targets that surpass their existing performance levels, drivers are motivated to actively engage in accepting more ride requests and meeting the increased demand. The bonus acts as a reward for their efforts and encourages them to go above and beyond.

This approach allows for an iterative and data-driven approach, enabling me to refine the pricing strategy based on real-world observations and feedback from users.

Further Considerations

Each month of the year experiences variations in demand due to various factors. It is important to consider the following elements:

- **Seasonal Patterns:** Different seasons often witness increased travel. For instance, during Christmas, there may be a rise in people flying to visit their families, while University of Toledo students may return home from vacations in summer.
- **Annual Events:** Major events throughout the year, such as Toledo Mud Hens baseball games, Toledo Jeep Fest, the Northwest Ohio Rib Off, and live concerts, can attract a significant influx of people.

During these times, it is likely that demand will surge, necessitating appropriate measures. One option would be to adjust the driver wage accordingly, such as raising it from $21 to $22, as an incentive for drivers to accept more ride requests during these peak periods. This approach aims to strike a balance manage demand fluctuations and provide reliable transportation services during high-demand periods.

Sources

- https://www.chargebee.com/blog/saas-metric-customer-life-time-cltv/#:~:text=Historical Customer Lifetime Value&text=This is how you can,is a relatively simple calculation.
- https://www.movoto.com/guide/toledo-oh/moving-to-toledo/
- https://ohiofestivals.net/ohio-festivals/toledo-festivals/
- https://en.wikipedia.org/wiki/Toledo,_Ohio