andrewskoehn@gmail.com February 2, 2023

Lyft Route Pricing – Case Study

Andrew Koehn

Problem

Lyft is launching in a new city: Toledo, Ohio. They need to select a wage to pay drivers for trips between the airport and downtown Toledo (one-way trips in either direction). They want to select the wage that maximizes their net revenue (the difference between the rider price and the wage paid to the driver) for the first 12 months of the launch.

Known Information

- Current market rate for the trip is $25 per ride (one-way, either direction). This price cannot change.
- Current market wage for the trip is $19 per ride (one-way, either direction) making Lyft's net revenue (or "take") $6 per ride.
    - At this wage, riders "match" with a driver 60 out of 100 times (meaning 60% of ride requests are fulfilled). This rate is called the match rate.
    - At this wage, drivers churn at 5% and fulfill roughly 100 rides per month.
- Riders request approximately one ride per month.
- Riders who never experience a failed ride request churn at 10%.
- Riders who experience one or more failed ride requests churn at 33%.
- Pricing experiments have shown that increasing the driver wage to $22/trip (meaning Lyft takes $3) increases the match rate to 93%.

Assumptions and Considerations

Lyft wants to maximize their net revenue, which is not affected by operating costs (profit analysis would consider costs). As such, this study does not consider the cost of acquiring the initial drivers and riders. This study also assumes that drivers and riders will not be replaced over time because costs to acquire new ones cannot be considered (as they do not affect revenue, only profit). Thus, this study assumes there are already enough drivers and riders to sustain a 12-month operation where each supply decreases each month based on its respective churn rate. Because rider churn is known to be constant, the study assumes that Lyft's initial rider supply will always be sufficient and will not affect the comparison of revenues. In other words, Lyft will never run out of riders regardless of the driver wage, but how many riders actually want to use Lyft will change due to churn. Because driver churn is variable, the study assumes that Lyft's initial driver supply will only be sufficient when the churn rate is 5% or less (per the current market conditions); this assumption will allow maximum revenues to be reliably compared since driver supply sufficiency is only guaranteed for certain churn rates. In other words, Lyft will never run out of drivers when the churn rate is 5% or less. If the churn rate at a certain wage is greater than 5%, Lyft may not have enough drivers for 12 months of operation.

Driver churn is variable, and it is reasonable to assume that it will decrease as wage increases; more drivers will stay with Lyft if they are being paid higher wages. It is also reasonable to assume the opposite - churn will increase if wage decreases. Thus, the effects of driver churn can be ignored when comparing revenues for wages of $19 or more (because churn will be 5% or less so the driver supply will be sufficient per study assumptions). Based on pricing experiments, this study hypothesizes that the maximum revenue will occur at a wage higher than $19. As long as that hypothesis holds true, driver churn will not affect the maximum relative revenue. If the maximum revenue is found to occur at a wage less than $19, driver churn will need to be considered since the churn rate may cause the initial supply of drivers to deplete (and thus the maximum revenue may not actually be attainable). Driver churn will be revisited if necessary after the data has been presented.

Pricing experiments indicate that increasing driver wages increases the match rate. It is reasonable to assume that the match rate will increase linearly with driver wages as long as the wage is above a certain threshold. Match rate will initially be very low when driver wages are low because no drivers will want to work. It will remain low until a certain minimum wage is met that some drivers feel is "enough" (for example, $12 per ride). As wage continues to increase, match rate will likely increase consistently as like-minded drivers start to accept the ride. Eventually, the wage will be high enough for most drivers, and increases in match rate will slow. Because $19-$22 per ride represents match rates from 60-93%, the study assumes that match rate increases linearly within and around that wage range (some drivers are already content with the wage, but there is still room for more to be enticed). Additionally, increasing driver wages is equivalent to decreasing Lyft's take per ride. As such, the study actually models match rate as a linear function of take (and not directly wage) because it more clearly relates to revenue. Market takes and corresponding match rates were used to derive the model from a system of linear equations (see Appendix A).

Data

Table 1 and Table 2 model revenue at different takes for the first 12 months of operation.

Column A in Table 1 has takes ranging from $10 to $2 (wages of $15-$23) in steps of $0.25. Column A in Table 2 has takes ranging from $4.25 to $3.75 (wages of $20.75-$21.25) in steps of $0.05.

Column B indicates the match rate for each take. The match rate is calculated with the following linear equation (see Appendix A for the derivation): match rate = (-0.11 * take) + 1.26.

Rider groups have different churn rates. Of riders who experience no issues, 10% will stop using Lyft each month. Of riders who experience one or more failed requests, 33% will stop using Lyft each month. As such, the actual churn rate is calculated with the following equation: (0.1 * match rate) + (0.33 * (1 – match rate)). This actual churn rate is indicated in Column C.

Columns D through O contain a relative revenue scalar for each month (M1 is Month 1, M2 is Month 2, and so on). The values themselves are not actual revenues; they are just numbers that can be used to reliably compare revenues (higher scalar = higher revenue). Actual revenues would require a known number of riders, which would be present in each month's revenue calculation and thus constant for all months. As such, the value does not affect the relative scalars used for comparing. Additionally, Lyft will lose riders each month; these riders will not be replaced. For each month after Month 1, only retained riders will use Lyft for rides. The number of retained riders is determined by multiplying the retention rate (1 – churn rate) by the previous month's number of retained riders. This calculation simplifies to just multiplying the retention rate by the previous month's revenue scalar (see Appendix B for derivation). In summary, Column D is calculated as (match rate) * (take); Columns E to O are calculated as (previous column) * (1 – churn rate).

Column P is the total revenue (relative scalar) for the 12 months. It is the sum of Columns D through O.

	A	B	C	D	E	F	M	N	O	P
1	Lyft's Take ($)	Match Rate	Monthly Rider Churn	M1 Revenue	M2 Revenue	M3 Revenue	M10 Revenue	M11 Revenue	M12 Revenue	Total Revenue
2	10	0.160	0.293	1.600	1.1309	0.7993	0.0704	0.0498	0.0352	5.372
3	9.75	0.188	0.287	1.828	1.3037	0.9297	0.0872	0.0622	0.0443	6.262
4	9.5	0.215	0.281	2.043	1.4695	1.0572	0.1055	0.0759	0.0546	7.140
5	9.25	0.243	0.274	2.243	1.6280	1.1816	0.1253	0.0910	0.0660	8.005
6	9	0.270	0.268	2.430	1.7790	1.3024	0.1468	0.1075	0.0787	8.856
7	8.75	0.298	0.262	2.603	1.9222	1.4194	0.1699	0.1255	0.0927	9.690
8	8.5	0.325	0.255	2.763	2.0574	1.5322	0.1947	0.1450	0.1080	10.508
9	8.25	0.353	0.249	2.908	2.1842	1.6405	0.2212	0.1661	0.1248	11.306
10	8	0.380	0.243	3.040	2.3025	1.7439	0.2493	0.1889	0.1430	12.084
11	7.75	0.408	0.236	3.158	2.4119	1.8421	0.2792	0.2132	0.1628	12.840
12	7.5	0.435	0.230	3.263	2.5123	1.9346	0.3106	0.2392	0.1842	13.571
13	7.25	0.463	0.224	3.353	2.6033	2.0211	0.3436	0.2668	0.2071	14.275
14	7	0.490	0.217	3.430	2.6847	2.1013	0.3781	0.2960	0.2317	14.950
15	6.75	0.518	0.211	3.493	2.7562	2.1747	0.4140	0.3267	0.2578	15.593
16	6.5	0.545	0.205	3.543	2.8175	2.2409	0.4512	0.3588	0.2854	16.201
17	6.25	0.573	0.198	3.578	2.8685	2.2996	0.4894	0.3923	0.3145	16.770
18	6	0.600	0.192	3.600	2.9088	2.3503	0.5285	0.4270	0.3450	17.298
19	5.75	0.628	0.186	3.608	2.9382	2.3926	0.5681	0.4627	0.3768	17.780
20	5.5	0.655	0.179	3.603	2.9564	2.4262	0.6082	0.4991	0.4096	18.212
21	5.25	0.683	0.173	3.583	2.9632	2.4505	0.6482	0.5360	0.4433	18.590
22	5	0.710	0.167	3.550	2.9582	2.4651	0.6878	0.5731	0.4776	18.908
23	4.75	0.738	0.160	3.503	2.9413	2.4696	0.7265	0.6100	0.5121	19.162
24	4.5	0.765	0.154	3.443	2.9122	2.4636	0.7638	0.6461	0.5466	19.345
25	4.25	0.793	0.148	3.368	2.8706	2.4465	0.7991	0.6811	0.5805	19.451
26	4	0.820	0.141	3.280	2.8162	2.4180	0.8317	0.7141	0.6132	19.473
27	3.75	0.848	0.135	3.178	2.7488	2.3775	0.8609	0.7447	0.6441	19.404
28	3.5	0.875	0.129	3.063	2.6682	2.3247	0.8859	0.7718	0.6724	19.236
29	3.25	0.903	0.122	2.933	2.5740	2.2589	0.9055	0.7946	0.6974	18.960
30	3	0.930	0.116	2.790	2.4661	2.1798	0.9188	0.8121	0.7179	18.566
31	2.75	0.958	0.110	2.633	2.3441	2.0868	0.9246	0.8231	0.7328	18.044
32	2.5	0.985	0.103	2.463	2.2078	1.9794	0.9216	0.8263	0.7408	17.384
33	2.25	1.013	0.097	2.278	2.0569	1.8571	0.9083	0.8201	0.7404	16.573
34	2	1.040	0.091	2.080	1.8911	1.7194	0.8831	0.8029	0.7300	15.598

Table 1: Total Revenue with Coarse Steps in Take (Columns G-L are hidden)

	A	B	C	D	E	F	M	N	O	P
1	Lyft's Take ($)	Match Rate	Monthly Rider Churn	M1 Revenue	M2 Revenue	M3 Revenue	M10 Revenue	M11 Revenue	M12 Revenue	Total Revenue
2	4.25	0.793	0.148	3.368	2.8706	2.4465	0.7991	0.6811	0.5805	19.451
3	4.20	0.798	0.146	3.352	2.8607	2.4417	0.8059	0.6878	0.5871	19.463
4	4.15	0.804	0.145	3.335	2.8504	2.4365	0.8125	0.6946	0.5937	19.471
5	4.10	0.809	0.144	3.317	2.8395	2.4308	0.8191	0.7012	0.6003	19.475
6	4.05	0.815	0.143	3.299	2.8281	2.4246	0.8255	0.7077	0.6067	19.476
7	4.00	0.820	0.141	3.280	2.8162	2.4180	0.8317	0.7141	0.6132	19.473
8	3.95	0.825	0.140	3.261	2.8038	2.4109	0.8379	0.7205	0.6195	19.467
9	3.90	0.831	0.139	3.241	2.7908	2.4033	0.8439	0.7267	0.6258	19.457
10	3.85	0.836	0.138	3.221	2.7774	2.3952	0.8497	0.7328	0.6320	19.443
11	3.80	0.842	0.136	3.200	2.7634	2.3866	0.8554	0.7388	0.6381	19.426
12	3.75	0.847	0.135	3.178	2.7488	2.3775	0.8609	0.7447	0.6441	19.404

Table 2: Total Revenue with Fine Steps in Take (Columns G-L are hidden)

Results

Looking at Table 1 Column P, there is a clear pattern between total revenue and take. Initially, as take decreases and match rate increases, total revenue increases. This trend makes sense; drivers are being paid more, so they fulfill more rides. More fulfilled rides means more retained riders, which means more possible riders the following month. More riders month-to-month means more overall rides and more revenue. This increasing revenue will continue as long as the increasing match rate (and thus retention rate) offsets the revenue lost by decreasing take. Once rider retention can no longer offset decreasing take, total revenue will begin to decrease; at some take and beyond, there is just not enough money per ride for Lyft to keep growing their revenue. The transition from increasing revenue to decreasing revenue is the take at which total revenue is maximized, and it occurs around row 26 near a take of $4 (cells highlighted in green). Table 1 models coarse take step sizes to find the approximate maximum revenue; Table 2 models fine take step sizes to find the actual maximum revenue. Looking at Table 2 Column P, it is clear that revenue is maximized in row 6 at a take of $4.05 (driver wage of $20.95). The total revenue scalar at $4.05 is 19.476, which is higher than all other total revenue scalars. Thus, total revenue appears to be maximized at a driver wage of $20.95 per trip.

It is important to consider why match rates increase in order to determine if a take is actually sustainable. Match rates can increase if rider demand decreases; this reason does not apply to the study because rider demand is constant. Match rates can increase if driver supply increases; this reason does not apply to the study because driver supply is actually assumed to be decreasing. Thus, under the study's assumptions, match rates must be increasing because driver output is increasing (how many rides per month a driver fulfills). At the identified take, the match rate has increased by 35% from 0.6 to 0.83. This change suggests that driver output must have increased by 35% as well. If drivers are fulfilling 100 rides per month when the match rate is 0.6, then drivers must be fulfilling 135 rides per month when the match rate is 0.83 (a 35% increase). According to Google Maps, the trip between the airport and downtown Toledo takes approximately 30 minutes. If drivers are completing 35 more trips per month, then they are working roughly 18 hours more per month. It is reasonable to believe that drivers could reliably work 18 hours more each month as they were only working 50 hours each month at $19/trip. 68 hours per month is significantly less than a standard full-time schedule of 160 hours per month, so it is safe to assume that the identified take and higher match rate (and thus maximum revenue) are sustainable.

Because the highest relative revenues all occur at driver wages greater than $19, the original assumption that the driver supply is sufficient is valid. As such, driver churn does not affect comparison of the higher relative revenues, and the maximum relative revenue can be confidently identified.

Recommendation

Given the results of this study, Lyft can maximize their 12-month revenue by increasing their driver wage from $19/trip to $20.95/trip ($1.95 more per trip). Increasing the wage will decrease Lyft's take from $6/trip to $4.05/trip, but increasing the match rate and lowering rider churn will yield the highest revenue.

This study made many assumptions, the largest of which was the match rate model. While the suggested driver wage is likely close to the actual wage needed to maximize revenue, more information could provide higher confidence in the model. If Lyft were to take one action to improve this study, they should invest in research on how driver wage affects driver output. Gaining information about how often drivers would work when paid different wages would be an easy and valuable step in helping predict match rate. If Lyft could more accurately model match rate, they could have higher confidence in selecting a wage that maximizes total revenue.

Additional Considerations

It is important to consider that maximum revenue does not correlate with maximum profit. Maximizing revenue does not involve cost analysis, so this study ignored all costs. Under those assumptions, maximum revenue occurred at a take of $4.05/trip; it is unknown whether that take could actually cover the cost of acquiring the initial drivers and riders needed to launch the ride. It is very possible that Lyft might actually need to take slightly more per trip in order to cover the cost of acquiring the drivers and riders in the first place. Further analysis would need to be (and should be) completed to maximize Lyft's profit and not just their revenue.

Appendix A

Match Rate Equation Derivation

$take_1 = \$6, \quad rate_1 = 0.6$

$take_2 = \$3, \quad rate_2 = 0.93$

$$0.6 = m(6) + b$$
$$b = 0.6 - 6m$$

$$0.93 = m(3) + b$$
$$0.93 = 3m + 0.6 - 6m$$
$$0.93 = -3m + 0.6$$
$$0.33 = -3m$$
$$m = -0.11$$

$$b = 0.6 - 6(-0.11)$$
$$b = 0.6 + 0.66$$
$$b = 1.26$$

$$\boxed{y = -0.11x + 1.26}$$

Appendix B

Revenue Scalar Derivation

MR = match rate , RR = retention rate

$M1 = \text{riders} \cdot MR \cdot \text{take}$

$M2 = (\text{riders} \cdot MR \cdot \text{take}) \cdot RR$

$M3 = ((\text{riders} \cdot MR \cdot \text{take}) \cdot RR) \cdot RR$

...

↓

riders is present in all → remove

↓

$M1 = MR \cdot \text{take}$

$M2 = M1 \cdot RR$

$M3 = M2 \cdot RR$

...

↓

$\boxed{\text{previous} \cdot RR}$