The impact of switching from variable to flat fare pricing for Collin County Transit

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Executive summary

Collin County Transit (CCT) offers a subsidized taxi voucher program to riders in participating cities. Currently, the service operates on a variable fare structure, whereby riders pay 25% of the trip price, and the remaining 75% is paid for by CCT.

CCT are interested in understanding the expected change in demand and cost that would result from switching from a variable fare structure to a fixed, flat rate. To investigate the impacts of this, Spare modelled future expected ridership growth for different trip lengths, under two different scenarios: a $2 flat fare and a $3 flat fare.

Key results from the modelling experiments are:

- Moving from a variable-fare model to a flat-fare model is expected to boost weekly ridership by 30–40%.
- A $2 flat fare will result in roughly 10% more trips than a $3 flat fare, but this ridership boost will cost 5% more per trip.
- The average cost to CCT for servicing all trips in a $2 flat fare scenario is $4,510 per week ($125,100 over 6 months). The average cost in a $3 flat fare scenario is $3,950 per week ($107,400 over 6 months).
- Under both flat fare scenarios, CCT wil save on costs servicing short trips, but will spend more on longer trips. When compared to today, total costs are expected to increase by 35% in a $2 flat fare scenario and by 19% in a $3 flat fare scenario.
- The **best value-for-money** option for CCT would be to introduce the **$3 flat rate.** This is not expected to boost ridership as much as a $2 flat rate, but the price per trip is expected to be lower.

Overview

The City of McKinney, the McKinney Urban Transit District (MUTD) and the Denton County Transportation Authority (DCTA) provide Collin County Transit, a subsidized taxi voucher program. Participating cities include Celina, Lowry Crossing, McKinney, Melissa, Princeton and Prosper.

CCT is planning to switch from a variable fare model to a flat fare model, for a period of 6 months later this year (May – October 2020).

CCT currently subsidizes 75% of the total cost of each taxi trip, with the remaining 25% being paid for by the rider. There will therefore be a financial impact to switching from this variable percentage-based model . While short trips will become less expensive for CCT to subsidize under a flat rate scenario, longer trips will become more expensive.

In this report, we consider two main pricing scenarios, informed by CCT's stated preferences:

1. A flat fare of $2 for all trips within Collin County;
2. A flat fare of $3 for trips in MUTD cities and $5 for trips in non-MUTD cities.

Methodology

To calculate the cost of running the service under a new pricing structure, we account for two main factors in our financial model:

1. The predicted underlying growth/decline in ridership based on historical data, regardless of whether pricing changed;
2. The expected growth/decline in specific types of rides in response to the change in pricing.

Data of ridership and trip prices were acquired from DCTA for the period January 2019 – March 2020, and these formed the basis for our historical analyses.

Over 12,400 trips were undertaken over fourteen months in the DCTA dataset. Long trips with uncommonly small prices were defined as outliers, and so 19 trips were removed from the dataset. The distribution of trips by price (which is correlated with distance) is shown in Figure 1.

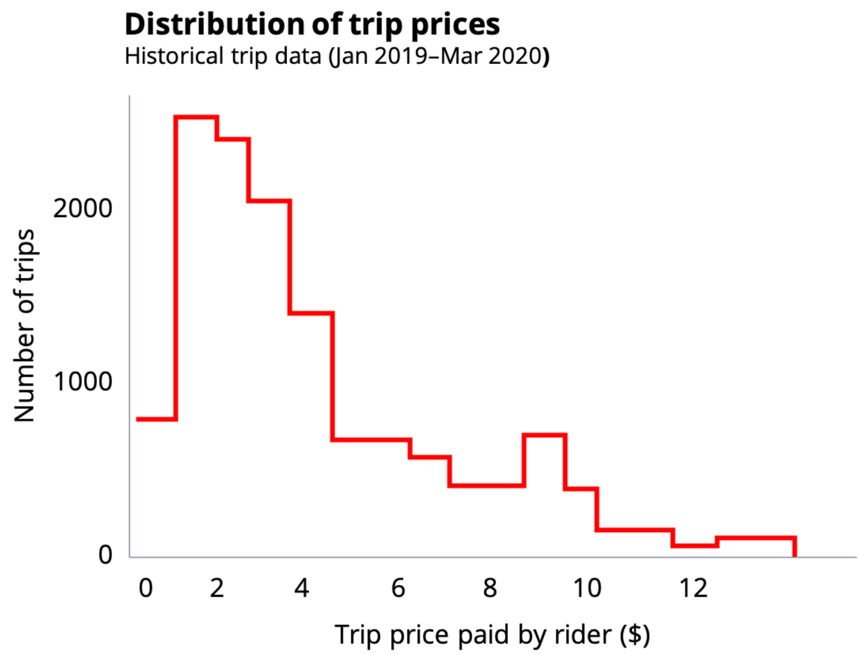

Figure 1. Distribution of historical trips by price paid by the rider (CCT pays the remaining 75%).

Only 55 trips were taken outside the MUTD zone ('private pay' trips), and most of them were undertaken by only a few individuals. The exceptionally small proportion of non-MUTD trips prevented us from reliably accounting for these in our model, so we only model MUTD trips.

A major point of consideration in any ridership forecasting model is the differentiation of trends for different trip lengths. Changes in demand will reflect the difference between the new flat fare and the current price of a trip. For instance, if a trip's price were to decrease under the new pricing regime, the propensity of riders to take such a trip would differ to a situation where a trip's price would increase (this is explored in more detail in the following sections).

To account for this, we divided trips into different price bands. In both scenarios, one price band encompasses all trips that would cost *more* in the new regime (i.e. all trips <$2 in scenario 1, and all trips <$3 in scenario 2). Of the remaining trips that would cost less in the new regime, we defined a 'low gains' category (trips costing more than $2 but less than $4 in scenario 1, and trips costing more than $3 but less than $5 in scenario 2), a 'medium gains' category (trips costing more than $4 but less than $9 in scenario 1, and trips costing more than $5 but less than $9 in scenario 2), and finally a 'big gains' category (trips costing more than $9 in both scenarios). These bands were defined according to the distribution of trips displayed in Figure 1.
As shown in Table 1, almost 75% of all trips taken with CCT are short trips costing less than $5. Under Scenario 1, a quarter of historical trips would end up paying more than they do

currently, whereas under Scenario 2, almost half of historical trips would end up paying more than they do currently.

Table 1. Statistics of trip price categories in each scenario.

Scenario	Trip price category (paid by rider)	Average trip price paid by rider ($)	Average number of trips per week	Proportion of all trips (%)	Average trip distance (miles)
Scenario 1 ($2 flat fare)	$2 or less	1.4	52	25	1.7
	$2–$4	2.9	82	40	4.7
	$4–$9	6.2	61	29	12.6
	$9+	10.2	14	6	19.7
Scenario 2 ($3 flat fare)	$3 or less	1.9	97	47	2.6
	$3–$5	3.7	53	25	6.3
	$5–$9	6.8	44	21	14.6
	$9+	10.2	14	6	19.7

Predicting change in baseline ridership from historical data

To model the baseline historical change in ridership *without* considering a price structure change, we built a Bayesian time series model using Prophet, a powerful open-source modelling Python library. We used Prophet to break down our data into temporal trends of varying length (from yearly to daily), and recombined them to create predicted weekly ridership until October 2020.

The historical and predicted total weekly ridership (at baseline, i.e. omitting the effect of the price changes) is shown in Figure 2. Similar forecast trends were produced for each price category (<$2, $2–$4, etc.), to predict baseline growth/decline at each tier. These baseline growth scenarios are then multiplied with an 'elasticity' factor to simulate the impact of price changes on each trip price category, as outlined in the next section.

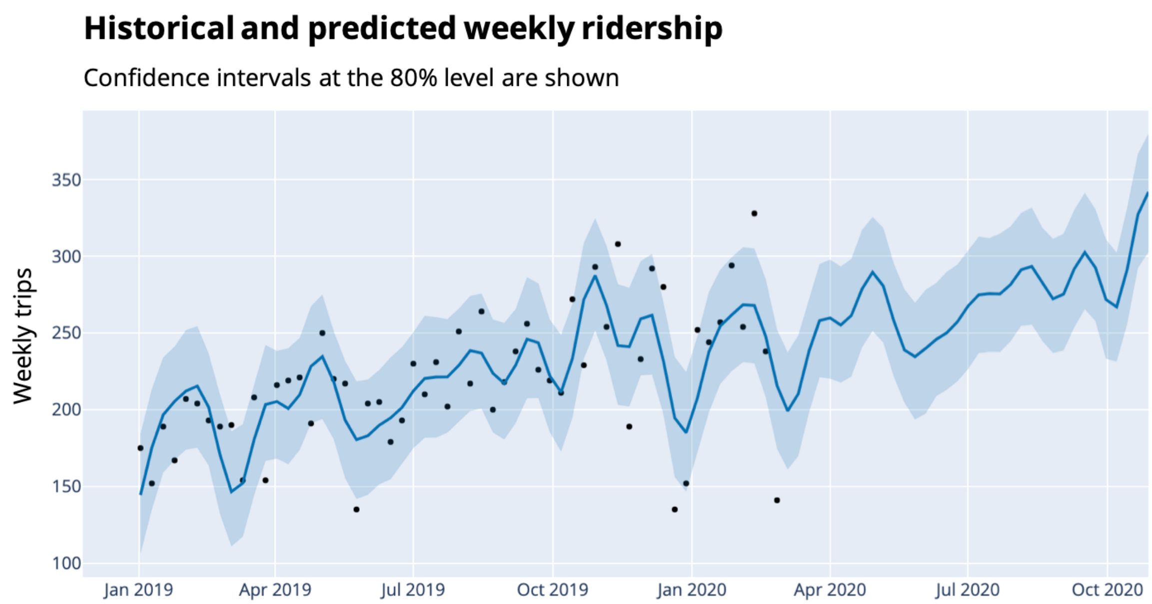

Figure 2. Historical and predicted weekly total ridership in Collin County, omitting price change effects.

Predicting change in ridership based on price sensitivity

The sensitivity of riders to transit pricing is traditionally measured using elasticities. Elasticities are the percentage change in consumption resulting from a one-percent change in price, all else held constant.

In the context of transit, a high elasticity value indicates that an individual's choice to ride transit *is* price-sensitive (i.e. a small change in price will dramatically affect how likely they are to ride transit). A low elasticity value indicates that prices have relatively little effect on ridership. Factors that affect transit elasticities include (described in detail in Appendix 1):

- User type
- Trip type
- Transit type
- Geography
- Type of price change
- Direction of price change
- Time period

While many of these are outside of the scope of this short study, we account for the *direction* of price change and the *time period* of changes. For the *direction of price change*, we note that price change elasticities are asymmetric: that is, an increase in fare will tend to cause greater ridership reduction than the same size fare reduction will increase ridership. We therefore choose asymmetric elasticities. For the *time period*, we consider the price impacts to be short-run (<2 years), as opposed to medium run (2–5 years) or long-run (5+ years). Short-run impacts are usually estimated to half as severe as long-run impacts.

A wide range of elasticity values are used in transit planning and academic studies to quantify the impact of price changes on transit. A comprehensive review of the literature is provided by Litman (2019)[1], whose recommendations are summarised by market segment and time period in Table 2.

Table 2. Elasticity values recommended by Litman (2019) for modelling response to transit fare changes.

Market segment	Short-term	Long-term
Overall	–0.2 to –0.5	–0.6 to –0.9
Peak	–0.15 to –0.3	–0.4 to –0.6
Off-peak	–0.3 to –0.6	–0.8 to –1.0
Suburban commuters	–0.3 to –0.6	–0.8 to –1.0

For our model, we chose an elasticity value of -0.35 for trip categories that will experience an *increase* in fare price, and a value of 0.25 for trip categories that will experience a *decrease* in fare price. This assumes short-term impacts, and balances the fact that many different trip types are taken on CCT, from commuting to recreation and socialising. This also closely matches a frequently-used rule-of-thumb, known as the Simpson–Curtin rule, which states that each 3% fare increase reduces ridership by 1%.

To calculate the impact of a fare change in ridership, we first consider the average trip price in each price category as the 'old price' (e.g. any rides in the <$2 category are given an 'old price' of $1.40, as shown in Table 1). Special care is required when calculating the impacts of large price changes, because each subsequent change impacts a different base in a compound way. Since this effect becomes significant when price changes exceed 50% (which will occur often in CCT's case), we compute elasticities using the appropriate 'arc elasticity' method[2]. As an example, a rise in average fare from $1.40 to $2 equates to a 42% increase; given an elasticity of -0.35, the arc elasticity is calculated as 1.42^(-0.35), multiplied by the old ridership. This results in a 12.5% decrease in ridership.

We do not assume a change in the average distances/prices taken in each trip category – we only calculate change in the number of trips taken in each category. In reality, lower prices may encourage riders to take slightly longer trips, which would push up the category averages. However, we assume this effect is relatively negligible to our overall results.

[1] Litman, T. (2019). https://www.vtpi.org/elasticities.pdf
[2] Pratt, R. (2004). http://www.trb.org/TRBNet/ProjectDisplay.asp?ProjectID=1034

Model results

We assess the two fare scenarios in turn, compare the costs of running each scenario to the current variable-fare model, and finally compare both scenarios to one another.

Scenario 1 ($2 flat fare)

The model results for scenario 1 are presented in Table 3. On average, 295 weekly trips are expected in this scenario, which represents a ~40% increase compared with today's service. The biggest cost to the agency will come from medium-length trips, which currently cost $4–$9 to riders. The average weekly cost to CCT for servicing all trips expected in this scenario will be $4,510, and the entire 6-month trial period will be expected to cost $125,100 to CCT.

Table 3. Scenario 1 ($2 flat fare): Model results for average demand. Costs to the agency represent the subsidy cost once the appropriate price has been paid by the rider.

	$2 or less	$2–$4	$4–$9	$9+	All categories
Total number of trips (6 months)	1150	3,400	3,000	530	**8050**
Average weekly trips	40	125	110	20	**295**
Total cost to agency (6 months)	$4,100	$32,300	$68,300	$20,400	**$125,100**
Average weekly cost to agency	$150	$1,100	$2,500	$760	**$4,510**

The average weekly costs incurred under the new price structure of a flat $2 fare are compared to the costs currently incurred in each price category (Table 4). While CCT will likely save on costs servicing short trips, the extra spending on longer trips will result in an overall weekly cost increase of approximately 35% compared to today.

Table 4. Scenario 1: Comparing agency costs under the new price structure and the current price structure.

	$2 or less	$2–$4	$4–$9	$9+	All categories
Current weekly cost to agency	$300	$950	$1,500	$580	**$3,330**
Weekly cost to agency under scenario 1	$150	$1,100	$2,500	$760	**$4,510**
Absolute weekly cost difference	-$150	$150	$1,000	$180	**$1,180**
Proportional weekly cost difference	-50%	+16%	+67%	+31%	**+35%**

Scenario 2 ($3 flat fare)

The model results for scenario 2 are presented in Table 5. On average, 270 weekly trips are expected in this scenario, which represents a ~30% increase compared with today's service. Like in scenario 2, the biggest cost to the agency will come from medium-length trips. The average weekly cost to CCT for servicing all trips expected in this scenario will be $3,950, and the entire 6-month trial period will be expected to cost $107,400 to CCT.

Table 5. Scenario 2 ($3 flat fare): Model results for average demand. Costs to the agency represent the subsidy cost once the appropriate price has been paid by the rider.

	$3 or less	$3–$5	$5–$9	$9+	All categories
Total number of trips (6 months)	2650	1900	2200	530	**7280**
Average weekly trips	100	70	80	20	**270**
Total cost to agency (6 months)	$12,000	$22,600	$52,400	$20,400	**$107,400**
Average weekly cost to agency	$450	$840	$1900	$760	**$3,950**

The average weekly costs incurred under the new price structure of a flat $3 fare are compared to the costs currently incurred in each price category (Table 6). CCT will likely save costs on trips that currently cost riders up to $5, but extra spending on longer trips will result in an overall weekly cost increase of approximately 19% compared to today.

Table 6. Scenario 2: Comparing agency costs under the new price structure and the current price structure.

	$3 or less	**$3–$5**	**$5–$9**	**$9+**	**All categories**
Current weekly cost to agency	$740	$800	$1,210	$580	**$3,330**
Weekly cost to agency under scenario 2	$450	$840	$1900	$760	**$3,950**
Absolute weekly cost difference	-$290	$40	$690	$180	**$620**
Proportional weekly cost difference	-39%	5%	57%	31%	**19%**

Comparing the two scenarios

Finally, we compare the performance of the service under the two proposed scenarios. Scenario 1 results in generally more trips than Scenario 2, but on average this ridership boost will cost 5% more per trip.

	Scenario 1 ($2 flat fare)	**Scenario 2 ($3 flat fare)**	**% difference (Scenario 2 vs 1)**
Total number of trips (6 months)	8050	7280	-10%
Average weekly trips	295	270	-9%
Total cost to agency (6 months)	$125,100	$107,400	-14%
Average weekly cost to agency	$4,510	$3,950	-12%
Average cost per trip to agency	$15.50	$14.75	-5%

Appendices

Appendix 1. Factors affecting transit demand elasticity

These descriptions are copied from Litman (2019).[3]

1. **User Type.** Transit dependent riders are generally less price sensitive than choice or discretionary riders (people who have the option of using an automobile for that trip). Certain demographic groups, including people with low incomes, non-drivers, people with disabilities, high school and college students, and elderly people tend to be more transit dependent. In most communities transit dependent people are a relatively small portion of the total population but a large portion of transit users, while discretionary riders are a potentially large but more price elastic transit market segment.
2. **Trip Type.** Non-commute trips tend to be more price sensitive than commute trips. Elasticities for off-peak transit travel are typically 1.5-2 times higher than peak period elasticities, because peak-period travel largely consists of commute trips.
3. **Geography.** Large cities tend to have lower price elasticities than suburbs and smaller cities, because they have a greater portion of transit-dependent users. Per capita annual transit ridership tends to increase with city size, as illustrated in Figure 1, due to increased traffic congestion and parking costs, and improved transit service due to economies of scale.
4. **Type of Price Change.** Transit fares, service quality (service speed, frequency, coverage and comfort) and parking pricing tend to have the greatest impact on transit ridership. Elasticities appear to increase somewhat as fare levels increase (i.e., when the starting point of a fare increase is relatively high).
5. **Direction of Price Change.** Transportation demand models often apply the same elasticity value to both price increases and reductions, but there is evidence that some changes are non-symmetric. Fare increases tend to cause a greater reduction in ridership than the same size fare reduction will increase ridership.
6. **Time Period.** Price impacts are often categorized as short-run (less than two years), medium run (within five years) and long-run (more than five years). Elasticities increase over time, as consumers take price changes into account in longer-term decisions, such as where to live or work. Long-run transit elasticities tend to be two or three times as large as short-run elasticities.
7. **Transit Type.** Bus and rail often have different elasticities because they serve different markets, although how they differ depends on specific conditions.

[3] Litman, T. (2019). https://www.vtpi.org/elasticities.pdf