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Transit Price Elasticities and Cross-Elasticities 17 June 2025

Todd Litman Victoria Transport Policy Institute



Abstract

This paper summarizes price elasticities and cross elasticities for use in public transit planning. It describes how elasticities are used, and summarizes previous research on transit elasticities. Commonly used transit elasticity values are largely based on studies of short- and medium-run impacts performed decades ago when real incomes where lower and a larger portion of the population was transit dependent. As a result, they tend to be lower than appropriate to model long-run impacts. Analysis based on these elasticity values tends to understate the potential of transit fare reductions and service improvements to reduce problems such as traffic congestion and vehicle pollution, and understate the long-term negative impacts that fare increases and service cuts will have on transit ridership, transit revenue, traffic congestion and pollution emissions.

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Introduction

Prices affect consumers' purchase decisions. For example, a particular product may seem too expensive at its regular price, but a good value when sold at a discount. Similarly, a price increase may cause consumers to choose another brand or product.

Such decisions are said to be "marginal," that is, the decision is at the margin between different alternatives and can therefore be affected by even small price changes. Although individually such decisions may be quite variable and difficult to predict (a consumer might succumb to a sale one day but ignore the same offer the next), in aggregate they tend to follow a predictable pattern: when prices decline consumption increases, and when prices increase consumption declines, all else being equal. This is called the "law of demand."

This paper summarizes research on how price changes affect transit ridership. *Price* refers to *users' perceived, marginal cost,* that is, the factors that directly affect consumers' purchase decision. This can include both monetary costs and non-market costs such as travel time and discomfort.

Price sensitivity is measured using *elasticities*, defined as the percentage change in consumption resulting from a one-percent change in price, all else held constant. A high elasticity value indicates that a good is price-sensitive, that is, a relatively small change in price causes a relatively large change in consumption. A low elasticity value means that prices have relatively little effect on consumption. The degree of price sensitivity refers to the absolute elasticity value, that is, regardless of whether it is positive or negative.

For example, if the elasticity of transit ridership with respect to (abbreviated *WRT*) transit fares is -0.5, this means that each 1.0% increase in transit fares causes a 0.5% reduction in ridership, so a 10% fare increase will cause ridership to decline by about 5%. Similarly, if the elasticity of transit ridership with respect to transit service hours is 1.5, a 10% increase in service hours would cause a 15% increase in ridership.

Economists use several terms to classify elasticity values. Unit elasticity refers to an elasticity with an absolute value of 1.0, meaning that price changes cause a proportional change in consumption. Elasticity values less than 1.0 in absolute value are called *inelastic*, meaning that prices cause less than proportional changes in consumption. Elasticity values greater than 1.0 are called *elastic*, meaning that prices cause more than proportional changes in consumption. For example, both a 0.5 and -0.5 values are considered *inelastic*, because their absolute values are less than 1.0, while both 1.5 and -1.5 values are considered *elastic*, because their absolute values are greater than 1.0. *Cross-elasticities* refer to percentage changes in consumption of a good caused by price changes in another related good. For example, automobile travel is complementary to vehicle parking and a substitute for transit travel, so an increase in the price of driving tends to reduce demand for parking and increase demand for transit.

Cross elasticities can be significant. Paulley, et al. (2006, p. 303) concluded that "...public transport use is remarkably sensitive to car costs, but car use is much less dependent on public transport costs." Fuel prices, parking fees and road tolls can have major impacts on transit ridership on affected corridors.

To help analyze cross-elasticities it is useful to estimate *mode substitution* factors, such as the change in automobile trips resulting from a change in transit trips. These factors vary depending on circumstances. For example, when bus ridership increases due to reduced fares, typically 10-50% of the added trips will substitute for an automobile trip. Other trips will shift from nonmotorized modes, ridesharing (which consists of vehicle trips that will be made anyway), or be induced travel (including chauffeured automobile travel, in which a driver makes a special trip to carry a passenger). Conversely, when a disincentive such as parking fees or road tolls causes automobile trips to decline, generally 20-60% shift to transit, depending on conditions. Pratt (1999) provides information on the mode shifts that result from various incentives, such as transit service improvements and parking pricing.

Special care is required when calculating the impacts of large price changes, or when predicting the effects of multiple changes such as an increase in fares and a reduction in service, because each subsequent change impacts a different base. For example, if prices increase 10% on a good with a –0.5 elasticity, the first one-percent of price change reduces consumption by 0.5%, to 99.5% of its original amount. The second one-percent price change reduces this 99.5% by another 99.5%, to 99.0%. The third one-percent of price change reduces this 99.0% by another 99.5% to 98.5%, and so on for each one-percent change. In total a 10% price increase reduces consumption 4.9%, not a full 5% that would be calculated by simply multiplying –0.5 x 10. This becomes significant when evaluating the impacts of price changes greater than 50%.

Price elasticities have many applications in transportation planning. They can be used to predict the ridership and revenue effects of changes in transit fares; they are used in modeling to predict how changes in transit service will affect vehicle traffic volumes and pollution emissions; and they can help evaluate the impacts and benefits of mobility management strategies such as new transit services, road tolls and parking fees.

Factors Affecting Transit Elasticities

Many factors can affect how prices affect consumption decisions. They can vary depending on how elasticities are defined, the type of good or service affected, the category of customer, the quality of substitutes, and other market factors (Alam, Nixon and Zhang 2015; Aston, et al. 2020; Chen and Naylor 2011; Dunkerley, et al. 2018). It is important to consider these factors in elasticity analysis.

Some factors that affect transit elasticities are summarized below.

- 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.
- *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.
- *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.



This graph illustrates the relationship between city size and annual per-capita transit travel for U.S cities between 200,000 and 3,000,000 population. Per capita ridership tends to grow with city size, due to increasing automobile costs and transit service efficiencies.

- *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).
- 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. A price increase or transit strike that induces households to purchase an automobile may be somewhat irreversible, since once people become accustomed to driving they often continue.



The absolute magnitude of elasticity values tend to increase over time. Long-run transit elasticities tend to be two or three times as large as short-run elasticities.

- *Time Period*. Price impacts are often categorized as short-run (less than two years), mediumrun (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, as illustrated in Figure 2. Long-run transit elasticities tend to be two or three times as large as short-run elasticities.
- *Transit Type*. Bus and rail often have different elasticities because they serve different markets, although how they differ depends on specific conditions. According to Paulley, et al. (2004), "Although car ownership has a negative impact on rail demand, it is less than for bus and, although there are quite large variations between market segments and across distance bands, the overall effect of income on rail demand is quite strongly positive. Rail income elasticities are generally found to be positive, and as high as 2 in some cases. As with the bus income elasticities, the rail elasticity can also be expected to increase over time." [as car ownership saturates]

Because there is significant difference in demand between dependent and discretionary riders we can say there is a "kink" in the demand curve (Clements 1997). As a result, elasticity values depend on what portion of the demand curve is being measured. Price changes may have relatively little impact on ridership for a basic transit system that primarily serves transit dependent users, but if the transit system wants to attract significantly more riders and reduce automobile travel, fares will need to decline and service improve to attract more price sensitive discretionary riders.

Coogan, et al. (2018) examine how various demographic, geographic and economic trends are likely to affect future transit demands, including ways that age, location, preferences, transit service quality, and availability of alternatives (including ride-hailing). The figures below illustrate examples of the analysis.









Summary of Transit Elasticity Studies

Many studies have been performed on the price elasticity of public transit, and several previous publications have summarized the results of such studies, including Alam, Nixon and Zhang (2015), Dunkerley, et al. 2018; Pham and Linsalata (1991); Oum, Waters, and Yong (1992); Goodwin (1992); Luk and Hepburn (1993); Pratt (1999); Dargay and Hanly (1999), TRACE (1999), Booz Allen Hamilton (2003), TRL (2004) and Watkins, et al. (2021). APTA (2008) summarizes a survey of U.S. transit agencies concerning the effects of recent fuel price increase on ridership. Significant results from this research are summarized below.

General Transit Fare Elasticity Values

A frequently-used rule-of-thumb, known as the *Simpson – Curtin* rule, is that each 3% fare increase reduces ridership by 1%. Like most rules-of-thumb, this can be useful for rough analysis but it is too simplistic and outdated for detailed planning and modeling.

Table 1 shows bus fare elasticity values published by the American Public Transportation Association which are widely used for transit planning in North America. This was based on a study of the short-run (less than two years) effects of fare changes in 52 U.S. transit systems during the late 1980s. Because they reflect short-run impacts and are based on studies performed when a larger portion of the population was transit-dependent, these values probably understate the long-run impacts of current price changes.

	Large Cities (More than One Million Population)	Smaller Cities (Less than One Million Population)			
Average for All Hours	-0.36	-0.43			
Peak Hour	-0.18	-0.27			
Off-Peak	-0.39	-0.46			
Off-peak Average	-0.42				
Peak Hour Average	-0.23				

Table 1Bus Fare Elasticities (Pham and Linsalata 1991)

This table summarizes U.S. transit fare elasticities published in 1991 by the APTA.

Erhardt, et al. (2022) analyzed how fare increases, low fuel prices, population declines in transit-oriented areas, plus increased incomes, car ownership, teleworking and ridehailing contributed to transit ridership declines in U.S. cities between 2012 and 2018. Dunkerley, et al. (2018) provides evidence on bus fare and journey time elasticities and diversion factors for all modes. They summarize key findings from analysis of numerous studies, as well as providing recommendations on values to be used in demand forecasting, appraisal and policymaking and identifying evidence gaps.

Iseki and Ali (2014) used panel data of transit ridership and gasoline prices for ten selected U.S. urbanized areas between 2002 and 2011 to analyze how gasoline prices affects ridership of four transit modes: bus, light rail, heavy rail, and commuter rail. Their analysis improves upon past studies on the subject, this study accounts for

endogeneity between the supply of services and ridership, and controls for a comprehensive list of factors that may potentially influence transit ridership. They found varying effects depending on transit modes and conditions. Strong evidence was found for positive short-term effects only for bus and the aggregate: a 0.61-0.62% ridership increase in response to a 10% increase in gasoline prices (elasticity of 0.061 to 0.062). However, the long-term effects was significant for all modes and indicated that a 10% fuel price increase caused a total ridership to increase from 0.84% for bus to 1.16% for light rail. The effects at the higher gasoline price level of over \$3 per gallon were found to be more substantial, with a ridership increase of 1.67% for bus, 2.05% for commuter rail, and 1.80% for the aggregate for the same level of gasoline price changes. Light rail shows even a higher rate of increase of 9.34% for gasoline prices was found for commuter and heavy rails, resulting in a substantially higher rate of ridership increase

The study, *Declines in Transit Ridership: Analysis of Recent Trends* (Watkins, et al. 2021) evaluated factors that affected U.S. transit ridership between 2012 and 2018. During that period, bus ridership declined 15% and rail ridership declined 3%. These losses are widespread and in contrast to trends in other countries. The study found that expanded transit service and land-use changes increased bus ridership 4.7% and rail ridership 10.7%, and transit operators that restructured their bus networks on average achieved 4.7% bus ridership increases above other service expansion gains. However, these increases were offset by other factors. Increased ride-hailing caused bus ridership, and rail ridership in mid-sized metropolitan areas to decline by 10%, but much smaller declines in larger cities. Lower gas prices, higher fares, higher incomes and car ownership and increased teleworking also contributed to transit ridership declines.

After a detailed review of international studies, Goodwin (1992) produced the average elasticity values summarized in Table 2. He noted that price impacts tend to increase over time as consumers have more options (related to increases in real incomes, automobile ownership, and now telecommunications that can substitute for physical travel). Nelson, et al (2006) found similar values in their analysis of Washington DC transit demand. Nijkamp and Pepping (1998) found elasticities in the –0.4 to –0.6 range in a meta-analysis of European transit elasticity studies.

	0000000000000000	/	
	Short-Run	Long-Run	Not Defined
Bus demand WRT fare cost	-0.28	-0.55	
Railway demand WRT fare cost	-0.65	-1.08	
Public transit WRT petrol price			0.34
Car ownership WRT general public transport costs			0.1 to 0.3
Petrol consumption WRT petrol price	-0.27	-0.71	-0.53
Traffic levels WRT petrol price	-0.16	-0.33	

Table 2 Transportation Elasticities (Goodwin 1992)

This table summarizes international transportation elasticities. Note that long-run effects (more than one year) are typically about twice short run effects. ("WRT" = With Respect To).

Dargay and Hanly (1999) studied the effects of UK transit bus fare changes over several years to derive the elasticity values summarized in Table 3. They used a dynamic econometric model (separate short- and long-run effects) of per capita bus patronage, per capita income, bus fares and service levels. They found that demand is slightly more sensitive to rising fares (-0.4 in the short run and -0.7 in the long run) than to falling fares (-0.3 in the short run and –0.6 in the long run), and that demand tends to be more price sensitive at higher fare levels. They found that the cross-elasticity of bus patronage to automobile operating costs is negligible in the short run but increases to 0.3 to 0.4 over the long run, and the long run elasticity of *car ownership* with respect to transit fares is 0.4, while the elasticity of *car use* with respect to transit fares is 0.3.

Table 3	Bus Fare Elasticities (Dargay and Hanly 1999, p. v					
Elastici	ty Type	Short-Run	Long-Run			
Non-urban		-0.2 to -0.3	-0.8 to -1.0			
Urban		-0.2 to -0.3	-0.4 to -0.6			

.. ...

This table shows elasticity values from a major UK study.

Dargay, et al. (2002) compared UK and French transit elasticities. They found that transit ridership declines with income (although not in Paris, where wealthy people are more likely to ride transit) and with higher fares, and increases with increased service. Table 4 summarizes their findings.

	Engl	England		се	
	Log-Log	Semi-Log	Log-Log	Semi-Log	
Income					
Short Run	-0.67	-0.69	-0.05	-0.04	
Long Run	-0.90	-0.95	-0.09	-0.07	
Fare					
Short Run	-0.51	-0.54	-0.32	-0.30	
Long Run	-0.69	-0.75	-0.61	-0.59	
Transit VKM					
Short Run	0.57	0.54	0.29	0.29	
Long Run	0.77	0.74	0.57	0.57	
Annual Fare Elasticity Growth Rate		1.59%		0.66%	

Table 4 Transit Elasticities (Dargay et al. 2002 table 4)

This table shows mean elasticity values based on 1975 to 1995 data.

With a log-log function elasticity values are the same at all fare levels, whereas with a semi-log function the elasticity value increases with higher fares. Log-Log functions are generally easiest to use and most common. Semi-log values are based on an exponential function, and can be used for predicting impacts of fares that approach zero, that is, if transit services become free, but are unsuited for very high fare levels, in which case

they may result in exaggerated elasticity values. For typical fare changes, between 10% and 30%, log-log and semi-log functions provide similar results, so either can be used.

Lee, Han and Lee (2009) found long-run elasticities of 0.25 for subway passenger trips and 0.32 for subway passenger kilometers with respect to fuel prices in Seoul, Korea between 2000 and 2008. Tsai, Mulley and Clifton (2014) used the Sydney Household Travel Survey data to identify public transport demand elasticities using a pseudo panel data approach. They estimate that Sydney's public transport price elasticity is -0.22 in the short run and -0.29 in the long run.

Table 5 summarizes short- and medium-term fare elasticities for the CityRail urban rail transit system in Sydney, Australia. Conditional fare elasticities refer to a situation where all CityRail fare levels are simultaneously increased by the same proportion. Ownprice elasticities refers to a situation where only one fare changes.

Table 5 Estimated S	5 Estimated Sydney CityRall Fare Elasticities (Booz & Co 2008)				
Ticket Type	Conditional	Own Price			
Single (Return)	-0.48	-0.56			
Off-Peak Return	-0.23	-0.30			
RailPass/FlexiPass	-0.28	-0.47			
TravelPass	-0.12	-0.39			
Total	-0.29	Not Applicable			

Table 5	Estimated S	ydney City	yRail Fare E	lasticities	(Booz & Co 2008)

Table 6 summarizes estimates of transit fare elasticities for different user groups and trips types, illustrating how various factors affect transit price sensitivities. For example, it indicates that car owners have a greater elasticity (-0.41) than people who are transit dependent (-0.10), and work trips are less elastic than shopping trips.

F	actor	Elasticity	
Overall transit fare	es	-0.33 to -0.22	
Riders under 16 ye	ears old	-0.32	
Riders aged 17-64		-0.22	
Riders over 64 yea	ars old	-0.14	
People earning <\$	5,000	-0.19	
People earning >\$15,000		-0.28	
Car owners		-0.41	
People without a car		-0.10	
Work trips		-0.10 to -0.19	
Shopping trips		-0.32 to -0.49	
Off-peak trips		-0.11 to -0.84	
Peak trips		-0.04 to -0.32	
Trips < 1 mile		-0.55	
Trips > 3 miles		-0.29	

Table 6 Transit Fare Elasticities (Gillen 1994, pp. 136-37)

This table shows transit fare elasticities disaggregated by rider and trip factors, which can be very useful for many types of transit and transport planning.

Rail and bus elasticities often differ. In major cities, rail transit fare elasticities tend to be relatively low, typically in the –0.18 range, probably because higher-income residents depend on such systems (Pratt 1999). For example, the Chicago Transportation Authority found that bus riders have elasticities of -0.30 during peaks -0.46 during off-peaks, while rail riders have elasticities of -0.10 during peaks and -0.46 off-peak. Fare elasticities may be relatively high on routes where travelers have viable alternatives, such as for suburban rail systems where most riders are discretionary.

Commuter transit pass programs, in which employers subsidize transit passes, can significantly increase ridership (Commuter Check, Commuter Choice). Deep Discount passes can encourage occasional riders to increase transit use or avoid ridership losses if implemented when fares are increasing (Oram and Stark 1996). Many campus UPass programs, which provide free or discounted transit fares to students and staff, have doubled or tripled the portion of trips made by transit (Brown, Hess and Shoup 2001).

Holmgren (2007) used meta-regression to explain the wide variation in elasticity estimates obtained in previous demand studies. He calculated short-run U.S. elasticities with respect to fare price (-0.59), level of service (1.05), income (-0.62), price of petrol (0.4) and car ownership (-1.48). The analysis indicates that commonly-used elasticity estimates treat transit service quality as an exogenous variable, which reduces analysis accuracy, and recommends that demand models include car ownership, price of petrol, own price, income and some measure of service among the explanatory variables, and that the service variable be treated as endogenous.

Table 7 summarizes travel demand elasticities developed for use in Australia, based on a review of various national and international studies. These standardized values are used for various transport planning applications throughout the country, modified as appropriate to reflect specific conditions.

Table / Australian Travel Demanu	Australian Traver Demand Elasticities (Luk & Repburn					
Elasticity Type	Short-Run	Long-Run				
Bus demand and fare	-0.29					
Rail demand and fare	-0.35					
Mode shift to transit and petrol price	+0.07					
Mode shift to car and rail fare increase	+0.09					
Road freight demand and road/rail cost ratio	-0.39	-0.80				
Petrol consumption and petrol price	-0.12	-0.58				
Travel level and petrol price	-0.10					

Table 7 Australian Travel Demand Elasticities (Luk & Hepburn 1993)

This table shows elasticity values adopted by the Australian Road Research Board.

Service Elasticities

Service elasticities indicate how transit ridership is affected by transit service quality factors such as convenience, frequency, speed and comfort (Kittleson & Associates, 2013; Phillips, Karachepone and Landis 2001; Greer and van Campen 2011).

Pratt (1999) finds that new bus service in a community with no previous transit service typically achieves 3 to 5 annual rides per capita, with 0.8 to 1.2 passengers per bus-mile. The elasticity of transit service expansion (routes into new areas) is typically 0.6 to 1.0, meaning that each 1% of additional transit vehicle-miles or vehicle-hours increases ridership 0.6-1.0%, with variations from less than 0.3 to more than 1.0. The elasticity of transit use with respect to transit service frequency (called a *headway elasticity*) averages 0.5, with greater effects where service is infrequent (Redelmeier and El-Geneidy 2024) There is a wide variation in these factors, depending on type of service, demographic and geographic factors. Higher service elasticities often occur with new express transit service, in university towns, and in suburbs with rail transit stations to feed. On the other hand, some service increases result in little additional ridership. It usually takes 1 to 3 years for new routes to reach their full potential ridership.

Portland, Oregon's *Streamline* program includes various transit operational improvements that improved service quality on designated Frequent Service routes (Koonce, et al. 2006). Between 1999 and 2005, when vehicle-hours on the twelve streamlined routes increased 16.3%, ridership on those routes increased 18.2%, while vehicle-hours on non-Frequent Service routes decreased 2.4% and ridership on those routes decreased 0.7%. This indicates an elasticity of 1.11 for the streamlined routes, that is, ridership increased proportionately more than the amount of service added. The change in ridership on the non-Frequent Service routes corresponds to an elasticity of 0.30; that is, each 1% change in service hours caused a 0.3% change in ridership. This elasticity is typical for urban systems with routes operating at 30-minute or better headways. Brechan (2017) evaluated the long-run effects on ridership of 89 Norwegian transit projects. The results indicate that increased service frequency tends to increase transit ridership more than fare price reduction projects

Approximately 35% more bus rapid transit (BRT) service is needed compared with rail service to attract the same peak-period ridership, indicating that rail passengers accept more crowding than on buses (Demery and Higgins 2002). Improved marketing, schedule information, easy-to-remember departure times, and more convenient transfers can also increase transit use, particularly where service is infrequent (Turnbull and Pratt 2003). Voith (1991) found that service elasticities tend to increase over time. He concludes, "The findings suggest that reductions in public transportation subsidies that result in higher fares and lower service quality may produce higher subsidy costs per rider than would be the case with higher total subsidy. Thus, the results from this analysis support the common public perception that raising public transit fares and reducing service simply reduce ridership, requiring further fare increases and service cuts."

Multi-Modal Models

Some researchers use elasticity and cross-elasticity data to create models that predict how various combinations of changes in transit services and fares, and vehicle operating costs, would affect transit ridership and automobile travel, and therefore their ability to help achieve strategic planning objectives such as congestion and emission reductions.

The METS (MEtropolitan Transport Simulator, IFS, 2001) is an urban transport demand simulation model available on the Internet (<u>http://vla.ifs.org.uk/models/mets22.html</u>). METS was developed in the early 1980s for use by the UK Department of Transport, and updated in 2000. It allows users to predict the changes in transit and automobile travel that would result from changes in transit service quality, frequency, fares and car costs.

Hensher developed a model of cross-elasticities between various forms of transit and car use, illustrated in Table 8. This type of analysis can be used to predict the effects that transit fare changes will have on vehicle traffic, and the effect that road tolls or parking fees will have on transit ridership. Such models tend to be sensitive to specific demographic and geographic conditions and so must be calibrated for each area.

Table 6 Direct and Cross-Share Elasticities (Henshel 1997, Table 8)							
	Train	Train	Train	Bus	Bus	Bus	Car
	Single Fare	Ten Fare	Pass	Single Fare	Ten Fare	Pass	
Train, single fare	-0.218	0.001	0.001	0.057	0.005	0.005	0.196
Train, ten fare	0.001	-0.093	0.001	0.001	0.001	0.006	0.092
Train, pass	0.001	0.001	-0.196	0.001	0.012	0.001	0.335
Bus, single fare	0.067	0.001	0.001	-0.357	0.001	0.001	0.116
Bus, ten fare	0.020	0.004	0.002	0.001	-0.160	0.001	0.121
Bus, pass	0.007	0.036	0.001	0.001	0.001	-0.098	0.020
Car	0.053	0.042	0.003	0.066	0.016	0.003	-0.197

Table 8Direct and Cross-Share Elasticities (Hensher 1997, Table 8)

This table indicates how changes in transit fares and car operating costs affect transit and car travel demand. For example, a 10% single fare train ticket increase will cause a 2.18% reduction in the sale of those fares, and a 0.57% increase in single fare bus tickets. This is based on a survey of residents of Newcastle, a small Australian city.

The Congressional Budget Office used highway traffic count data to conclude that fuel price increases can cause modal shifts (CBO 2008). They find that a 20% gasoline price increase reduces traffic volumes on highways with parallel rail transit service by 0.7% on weekdays and 0.2% on weekends, with comparable increases in transit ridership, but find no traffic reductions on highways that lack parallel rail service. Currie and Phung (2008) found that in Australia, the cross elasticity of transit ridership with respect to fuel prices are 0.22, with higher values for high quality transit (Rail/BRT) and for longer-distance travel, and lower values for basic bus service and shorter-distance trips.

TRACE (1999) provides detailed elasticity and cross elasticity estimates for various types of travel (car-trips, car-kilometers, transit travel, walking/cycling, commuting, business, etc.) and conditions, based on numerous European studies. Comprehensive sets of elasticity values such as these can be used to model the travel impacts of various combinations of price changes, such as a reduction in transit fares combined with an increase in fuel taxes or parking fees. It estimates that a 10% rise in fuel prices increases transit ridership 1.6% in the short run and 1.2% over the long run, depending on regional vehicle ownership. This declining elasticity value is unique to fuel, because fuel price increases cause motorists to purchase more fuel efficient vehicles. Table 9 summarizes elasticities of trips and kilometers with respect to fuel prices in areas with high vehicle ownership (more than 450 vehicles per 1,000 population).

Table 9 Elasticities WRT Fuel Price (TRACE 1999, Tables 6 & 9)					
Term/Purpose	Car Driver	Car Passenger	Public Transport	Slow Modes	
Trips					
Commuting	-0.11	+0.19	+0.20	+0.18	
Business	-0.04	+0.21	+0.24	+0.19	
Education	-0.18	+0.00	+0.01	+0.01	
Other	-0.25	+0.15	+0.15	+0.14	
Total	-0.19	+0.16	+0.13	+0.13	
Kilometers					
Commuting	-0.20	+0.20	+0.22	+0.19	
Business	-0.22	+0.05	+0.05	+0.04	
Education	-0.32	+0.00	+0.00	+0.01	
Other	-0.44	+0.15	+0.18	+0.16	
Total	-0.29	+0.15	+0.14	+0.13	

Table 9Elasticities WRT Fuel Price (TRACE 1999, Tables 8 & 9)

Slow Modes = Walking and Cycling WRT = With Respect To

This table shows the estimated elasticities and cross-elasticities of urban travel in response to a change in fuel price or other vehicle operating costs.

Table 10	Parking Price Elasticities	(TRACE 1999, Tables 32 & 33))
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Term/Purpose	Car Driver	Car Passenger	Public Transport	Slow mode
Trips				
Commuting	-0.08	+0.02	+0.02	+0.02
Business	-0.02	+0.01	+0.01	+0.01
Education	-0.10	+0.00	+0.00	+0.00
Other	-0.30	+0.04	+0.04	+0.05
Total	-0.16	+0.03	+0.02	+0.03
Kilometres				
Commuting	-0.04	+0.01	+0.01	+0.02
Business	-0.03	+0.01	+0.00	+0.01
Education	-0.02	+0.00	+0.00	+0.00
Other	-0.15	+0.03	+0.02	+0.05
Total	-0.07	+0.02	+0.01	+0.03

Slow Modes = Walking and Cycling WRT = With Respect To

This table indicates how parking prices affect travel by automobile, public transit and slow modes.

Frank, et al. (2008) evaluate the effects of relative travel time on mode choice. They find that, walking and biking will be used for shorter trips, such as travel to local stores and mid-day tours from worksites if services are nearby, and rates of transit use are more sensitive to changes in travel time than fare levels, with wait time much more "costly" than in-vehicle time. Their analysis suggests that a considerable growth in transit ridership could be achieved through more competitive travel times on transit.

Parking prices and road tolls tend to have a greater impact on transit ridership than other vehicle costs such as fuel, typically by a factor of 1.5 to 2.0, because they are paid directly on a per-trip basis. Table 11 shows how parking prices affects travel in a relatively automobile-oriented urban region.

		J · · · /		
	Preferred CBD	Less Preferred CBD	CBD Fringe	
Car Trip, Preferred CBD	-0.541	0.205	0.035	
Car Trip, Less Preferred CBD	0.837	-0.015	0.043	
Car Trip, CBD Fringe	0.965	0.286	-0.476	
Park & Ride	0.363	0.136	0.029	
Ride Public Transit	0.291	0.104	0.023	
Forego CBD Trip	0.469	0.150	0.029	

 Table 11
 Parking Elasticities (Hensher and King 2001, Table 6)

This table shows elasticities and cross-elasticities for changes in parking prices at various Central Business District (CBD) locations. For example, a 10% increase in prices at preferred CBD parking locations will cause a 5.41% reduction in demand there, a 3.63% increase in Park & Ride trips, a 2.91 increase in Public Transit trips and a 4.69 reduction in total CBD trips.

Hensher and King (1998) calculate elasticities and cross-elasticities for various forms of transit fares and automobile travel in central Sydney, Australia, as summarized in Table 12. Fearnley and Bekken (2005) summarize elasticity research and calculate the ratio of short- to long-run effects, as summarized in Table 12.

Table 12 Inalisit Llasticities (Learniey and Derken 2000)				
	Short-run Elasticity	Long-run Elasticity	Long-Run/Short-Run	
Service Level, Local Public Transport	0.43	0.75	1.84	
Fare Level, Local Public Transport	-0.44	-0.76	1.92	
Fare Level, Train/Metro	-0.61	-0.98	1.59	
Average Ratio long-run/short-Run			1.84	

Table 12Transit Elasticities (Fearnley and Bekken 2005)

Fehr & Peers (2004) develop "Direct Ridership Models" for predicting the effects of various changes on transit ridership, based on regression analysis of various North American transit systems. Table 13 provides examples of their results.

Table 13 Impacts on Transit Ridership (Feh	Impacts on Transit Ridership (Fehr & Peers 2004)				
Given a 100% Increase In	Expect Ridership Increase				
Population and employment within ½ mile of transit station.	23%				
Population within station catchment.	2%				
Number of peak period trains.	48%				
Peak-period feeder buses.	29%				
Parking spaces.	4%				

This table shows how various transit system changes affect transit ridership.

Currie and Justin Phung (2007) calculated the aggregate cross-elasticity of US transit demand with respect to fuel price (e) to be 0.12, indicting that transit demand increases 1.2% for every 10% gas price increase. US light rail is particularly sensitive to gas prices, with values for (e) measured at 0.27 to 0.38. Bus ridership is only slightly sensitive to gas prices (e= 0.04) and heavy rail is higher (0.17) which is consistent with most international evidence. A longitudinal model suggests some acceleration in transit mode sensitivity.

Mattson (2008) analyzed fuel price increase impacts on transit ridership in U.S. cities. He found longer-run elasticities of transit ridership with respect to fuel price are 0.12 for large cities, 0.13 for medium-large cities, 0.16 for medium-small cities, and 0.08 for small cities. These values are similar to previous estimates from other studies. For large and medium-large cities, the response is fairly quick, mostly occurring within one or two months after the price change, while for medium and small cities, the effects take five to seven months. The quicker response in larger cities may be explained by the fact that large city residents are generally more accustomed to public transport and so are quicker to shift mode than in smaller cities where transit use is uncommon. The elasticity is lowest for the smallest cities, indicating that people in small urban or rural areas are less likely to switch to transit. Medium-small cities have the highest response.

Lane (2008) analyzed the relationships between fluctuations in gas prices and transit ridership in nine U.S. cities between June 2001 and September 2006. He found a statistically strong positive relationship, particularly in cities with rail transit systems. He developed a model which predicts how much transit demand would increase given a particular increase in fuel prices, as summarized in Table 14.

City	\$∠	4.00	\$5.00		\$6.00	
	Fuel	Transit	Fuel	Transit	Fuel	Transit
Los Angeles	20.65%	6.21%	43.13%	14.36%	65.99%	23.97%
Chicago	22.26%	8.72%	45.03%	18.94%	68.21%	30.27%
Boston	29.11%	6.53%	53.16%	14.49%	77.63%	23.44%
San Francisco	23.82%	3.76%	46.89%	9.68%	70.36%	17.07%
Miami	26.65%	10.88%	50.24%	23.70%	74.25%	37.93%
Seattle	29.27%	10.31%	53.35%	22.66%	77.85%	36.50%
Houston	36.57%	12.24%	62.01%	26.15%	87.90%	41.31%
Denver	29.20%	17.97%	53.26%	35.70%	77.75%	53.50%
Cleveland	36.82%	18.67%	62.31%	36.83%	88.24%	54.91%

Table 14Fuel Price Impacts on Transit Ridership (Lane 2008)

This table indicates the percentage increases in fuel prices and transit ridership that can be expected from \$4.00, \$5.00 and \$6.00 fuel prices in various U.S. cities.

APTA (2011) used data from previous studies and recent experience by U.S. transit agencies to evaluate how transit ridership would grow in response to increased fuel prices. Regular gasoline prices increased 35% from \$3.053 per gallon on 31 December 2007 to a peak of \$4.114 on 7 July 2008, then declined 61% to \$1.613 on 27 December 2008. Transit ridership increased during this period, with a 3.42% increase during the first quarter, 5.19%, and 6.52% during the third quarter, indicating a lag between fuel price and transit ridership changes. Based on this research they developed a model that predicts how annual transit ridership is expected to increased using low, average, and high elasticity values.

Haire and Machemehl (2007) found similar results. Analyzing ridership in five U.S. cities they found statistically significant correlation between ridership and fuel prices, suggesting that rising fuel prices increased transit use in historically auto-oriented American cities. They estimate that, on average, a one percent fuel price rise increases transit demand approximately 0.24 percent, or approximately 0.09 percent ridership gain for each additional cent of fuel price. Maley and Weinberger (2009) found that in Philadelphia, fuel price increases had a larger effect on regional rail ridership (0.27 to 0.38 elasticities) than on local bus ridership (0.15 to 0.23 elasticities), probably due to a larger portion of rail riders being discretionary transit users who have the option of driving, and so are more likely to do so when fuel prices decline.

Lunke, Fearnley and Aarhaug (2021) analyzed how public transit service quality factors affect urban rail ridership in Norway. They found that high transit mode shares require a set of quality factors including travel times that are competitive compared with driving, direct routes or few transfers, and high service frequency. If any of these are not in place public transit market share decline significantly.

Blanchard (2009) used regional gasoline prices, transit ridership and supply data from 218 US cities from 2002 to 2008 to estimate the cross elasticity of demand for four transit modes with respect to gasoline price. The results indicate that the cross-price elasticity of transit demand with respect to gasoline price ranges from -0.012 to 0.213 for commuter rail, -0.377 to 0.137 for heavy rail, -0.103 to 0.507 for light rail, and 0.047 to 0.121 for bus. The values vary significantly between cities, but are not highly correlated with urban population size, and the cross-price elasticity increased over this time period for commuter rail, light rail, and motorbus transit.

Jung, et al. (2016) used a data set of debit and credit card transactions in Korea to examine the effect of gasoline prices on individual choices between private vehicle and public transit travel. The study found significant heterogeneity, with some people being much more price sensitive than others.

Brand (2009) found that the 20% U.S. fuel price increase between 2007 and 2008 caused a 3.5% VMT reduction, indicating a short-run price elasticity ranging from -0.12 to -0.17. Accounting for base trends (between 1983 and 2004 VMT increased about 2.9% annually and gasoline consumption about 1.2% annually, reflecting population, income and GDP growth) the short-run VMT fuel price elasticity ranged from -0.21 to -0.30. During this period, transit ridership increased about 4%. This increase was widespread, with 86% of transit agencies reporting ridership increases. Comparing the transit ridership increase to VMT decline indicates that only about 5% of the reduced vehicle travel shifted to transit, although this shift was much greater in major cities with high quality public transit services. For example, in New York City traffic declined 6.3% through the Lincoln and Holland Tunnels, and more than 7% on four major bridges. Greer and van Campen (2011) found that each 1% reduction in cars per household increases public transit ridership about 0.763% in Auckland, New Zealand.

Using data from the San Francisco Bay region, Sun (2016) found the elasticity of transit ridership with respect to fuel prices ranges between 0.0581-0.147, with the highest elasticity values for Bus, followed by Light Rail, and least for Heavy Rail. The paper suggests that transit authorities adjust service schedules in response to fuel price changes to improve service standards.

The Puget Sound *Traffic Choices Study* measured how 275 volunteer motorists responded to road pricing (PSRC 2005). Each participant was given a \$1,016 debit account. A meter in their car and which tracked where and when they drive and subtracted tolls that varied depending on time and location. The results indicate that participants changed trip time, route, frequency and distance in response. Total vehicle travel declined about -0.12. The elasticity of Home-to-Work travel averaged approximately -0.04 overall, but was four times higher (-0.16) for workers with the best public transit service, indicating that the cross-elasticity of vehicle travel with respect to price is affected by transit service quality.

Conclusions and Recommendations

An important conclusion of this research is that no single transit elasticity value applies in all situations: various factors affect price sensitivities including type of user and trip, geographic conditions and time period.

Available evidence suggests that the elasticity of transit ridership with respect to fares is usually in the –0.2 to –0.5 range in the short run (first year), and increases to –0.6 to – 0.9 over the long run (five to ten years). These are affected by the following factors:

- Transit price elasticities are lower for transit dependent riders than for discretionary ("choice") riders.
- Elasticities are about twice as high for off-peak and leisure travel as for peak and commute travel.
- Cross-elasticities between transit and automobile travel are relatively low in the short run (0.05), but increase over the long run (probably to 0.3 and perhaps as high as 0.4).
- A relatively large fare reduction is generally needed to attract motorists to transit, since they are discretionary riders. Such travelers may be more responsive to service quality (speed, frequency and comfort), and higher automobile operating costs through road or parking pricing.
- Due to variability and uncertainty it is preferable to use ranges rather than point values for elasticity analysis.

Commonly used transit elasticity values primarily reflect short- and medium-run impacts and are based on studies performed 10-40 years ago, when real incomes where lower and a greater portion of the population was transit dependent. The resulting elasticity values may be appropriate for predicting how a change in transit fares or service will affect next year's ridership and revenue, but long-run elasticity values are more appropriate for strategic planning. Conventional traffic models that use standard elasticity values based on short-run price effects tend to understate the potential of transit fare reductions and service improvements to reduce problems such as traffic congestion and vehicle pollution. Conversely, these models will understate the longterm negative impacts that fare increases and service cuts can have on transit ridership, transit revenue, traffic congestion and pollution emissions.

In most communities (particularly outside of large cities) transit dependent people are a relatively small portion of the total population, while discretionary riders (people who have the option of driving) are a potentially large but more price sensitive market segment. As a result, increasing transit ridership requires pricing and incentives that attract travelers out of their car. Combinations of fare reductions and discounted passes, higher vehicle user fees (such as priced parking or road tolls), improved transit

service, and better transit marketing can be particularly effective at increasing transit ridership and reducing automobile use (Brechan 2017).

Transit planners generally assume that transit is price inelastic (elasticity values are less than 1.0), so fare increases and service reductions increase net revenue. This tends to be true in the short-run (less than two years), but long-run elasticities approach 1.0, so financial gains decline over time.

Not all of the increased transit ridership that results from fare reductions and service improvements represents a reduction in automobile travel. Much of this additional ridership may substitute for walking, cycling or rideshare trips, or consist of absolute increases in total personal mobility. In typical situations, a quarter to half of increased transit ridership represents a reduction in automobile travel, but this varies considerably depending on specific conditions.

Table 15 summarizes recommended generic values based on this research. These values reflect the results of numerous studies, presented in a format to facilitate their application in typical transport planning situations. High and low values are presented to allow sensitivity analysis, or a midpoint value can be used. Actual elasticities vary depending on circumstances, so additional review and research is recommended to improve and validate these values, and modify them to specific situations.

	Market Segment	Short Term	Long Term
Transit ridership WRT transit fares	Overall	–0.2 to –0.5	–0.6 to –0.9
Transit ridership WRT transit fares	Peak	–0.15 to –0.3	–0.4 to –0.6
Transit ridership WRT transit fares	Off-peak	–0.3 to –0.6	–0.8 to –1.0
Transit ridership WRT transit fares	Suburban Commuters	–0.3 to –0.6	–0.8 to –1.0
Transit ridership WRT transit service	Overall	0.50 to 0.7	0.7 to 1.1
Transit ridership WRT auto operating costs	Overall	0.05 to 0.15	0.2 to 0.4
Automobile travel WRT transit costs	Overall	0.03 to 0.1	0.15 to 0.3

Table 15 Recommended Transit Elasticity Values

This table summarizes recommended values resulting from this study. These values should be modified as appropriate to reflect specific conditions. (WRT = With Respect To)

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