

1 **It's a matter of time: An assessment of additional time budgeted for**
2 **commuting across modes**

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1 ABSTRACT

2 Commute travel time is not always reliable, and individuals often budget additional time to ensure
3 that they arrive at their destination punctually. As a result, people lose unnecessary extra time in
4 travelling. This study investigates the amount of additional time commuters allocate to account for
5 travel time unreliability and presents the results using a series of log-linear regression models. Data
6 for this study originate from the 2013 McGill Commuter Survey, a university-wide survey in which
7 students, staff and faculty described their typical commuting experience to McGill University,
8 located in Montreal, Canada. Results reveal that drivers allocate the most extra time for their
9 commute, while users of other modes (transit users, cyclists and pedestrians) budget about 27 to
10 64% less than drivers. The findings of this study also indicate that bus commuters add 13% more
11 buffer time per bus taken, while train users budget 12% less time for every commuter train taken.
12 These findings reveal an existing perception that the street network is unreliable (either when using
13 buses or cars). Hence, the city should consider implementing strategies such as exclusive bus lanes,
14 and variable cost congestion price charging schemes to reduce uncertainty in travel time and
15 improve the reliability of the street network. Such strategies are expected to decrease the level of
16 uncertainty related to commuting to work/school and accordingly reduce the amount of time lost
17 due to additional time budgeted for uncertainty.

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Keywords: Travel time reliability, Network reliability, Travel time budget, Commute

1 INTRODUCTION

2 Although prior experience helps individuals anticipate events that may arise during their commute,
3 there is always a degree of uncertainty in the travel duration and ultimately arrival time at
4 destinations. In Montreal, Canada, the most recent census statistics show an average commuting
5 time of nearly 30 minutes (1). Within the population, however, 24% spend more than 45 minutes
6 commuting. Additionally, based on a 30-minute car commute in Montreal, a driver is expected to
7 experience 21 minutes of delay, which is equivalent to 79 hours per year (2). If transportation
8 planners and policy makers understand how commuters respond to travel time uncertainty, they
9 can generate appropriate performance indicators to evaluate transportation networks as well as
10 implement policies that effectively improve the travel experience of residents and reduce lost time
11 that people add to their commute due to uncertainty.

12 When faced with uncertainty in travel time, researchers have found that commuters adjust
13 their departure time by leaving early (3-6), altering travel routes (7-9) and/or switching their
14 transportation mode (10; 11). While there are three distinct strategies to mitigate the risk of travel
15 time unreliability, this paper focuses specifically on the first method of adjusting departure time to
16 allocate extra travel time, thereby minimizing the consequences of variability in travel duration.
17 Though many previous studies have relied on stated-preference experiments to determine
18 individuals' behavioral reactions to travel time variability in hypothetical scenarios (12-14), few
19 have studied this topic using data from real-life situations with a comparison across different
20 modes.

21 This study uses empirical data from a university travel survey to quantify how much extra
22 time commuters allocate to buffer against unexpected circumstances and delays. Based on their
23 typical commuting patterns to McGill University, respondents reported the number of additional
24 minutes they budget to ensure that they arrive at their destination on time. The objective of this
25 study is to investigate the relationship between the variation of travel time contingency and the
26 characteristics of the commute across different modes.

27 The paper begins with a review of existing literature about travel time reliability, and
28 continues with descriptions of the data and methods used in this study. The results of the log-linear
29 regression models are then presented and discussed. Finally, the paper concludes with
30 recommendations for policy and future research.

31 LITERATURE REVIEW

32 What is Travel Time Reliability?

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34 Travel time reliability, a dimension of network reliability, is defined as the consistency of travel
35 duration between an origin and destination or the probability that a trip between two specific
36 locations in a network can occur within a quantified time frame (15-17). In other words,
37 transportation networks with high travel time reliability have low travel time variability. Sources
38 of variations in travel time, as proposed by Wong and Sussman (18), include (a) predictable
39 variations between time of day, different seasons, and days of week, (b) unpredictable variations
40 due to network interruptions such as accidents, and other (c) random minor variations occurring,
41 for example, due to the synchronization of traffic lights. Related to Wong and Sussman (18)'s
42 sources of predictable variations, Nicholson and Du (19) suggested that variations in travel time
43 can also result from fluctuations in the demand and supply of the system. For instance, in a public
44 transit network, both the frequency of service and the number of passengers boarding and
45 alighting, which typically differ based on time of day and day of the week, have an effect on the
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1 travel duration that an individual experiences. As commuters become familiar with their
2 commuting trips, it is expected that they are able to foresee and adjust for predictable variations
3 such as peak-hour congestion (20). Contrastingly, unpredictable variations (network interruptions)
4 such as car accidents and human-caused delays (e.g. metro riders keeping the doors open, personal
5 belongings falling onto the track), are more difficult to account for (21), and are what characterizes
6 travel time reliability of transportation networks (22). It is important to maintain high travel time
7 reliability of networks, as studies have shown that costs associated to uncertainty in travel time
8 (described in the next section) can trigger changes in travel behavior (21; 23; 24). People account
9 for travel time unreliability by adding more time to their commute to ensure on-time arrival at a
10 destination. This additional time is discussed in more detail in the following section.

11 **What are the Impacts of Unreliable Travel Time? How Do Individuals Respond?**

12 Unreliable travel time results in a mismatch in the desired arrival time and the actual arrival time,
13 and real consequences may affect commuters with temporal restrictions more severely (5; 6; 25;
14 26). Individuals may experience extended waiting times, miss a connection, have difficulty in
15 finding comfortable seating, or face penalties associated to being late for work (22). In addition to
16 these consequences, there is an inherent cost related to travel time uncertainty itself; travel time
17 unreliability may cause individuals to experience heightened levels of anxiety or stress as well as
18 dissatisfaction with the transportation system they are using (11; 27). Undoubtedly, individuals
19 traveling on trips with temporal constraints value travel time reliability highly (28).

20 Gaver (3), one of the pioneers in this growing field of research, proposed a theoretical
21 framework in which individuals would start their trip at an earlier time to accommodate travel time
22 variability. Knight (4) followed with his hypothesis of a “safety margin” which commuters allocate
23 to reduce their probability of arriving late to work. The underlying assumption in these studies is
24 that early arrivals are preferable over late arrivals. In a more recent study, Noland et al. (26) used
25 data from a stated-preference survey to evaluate how travel time unreliability influences departure
26 time choice for drivers. They found that increased travel time variability resulted in earlier
27 departures, confirming findings from previous studies.

28 Stated-preference surveys have also been used to investigate the impact of travel time
29 unreliability on route choices. In their analysis, Jackson and Jucker (7) found that commuters
30 prefer the route with higher travel time consistency, even if total journey time is greater than a
31 shorter route with more variability. Furthermore, Abdel-Aty, Kitamura and Jovanis (9) found that
32 the availability of traffic information has the potential in influencing drivers to choose an
33 alternative route. Similarly, Brownstone et al. (29) evaluated revealed-preference data from the
34 San Diego I-15 congestion-pricing project and found that drivers increased their usage of the toll
35 facility when the prices were highest to reduce travel time. Based on their results, they concluded
36 that drivers are anxious about unanticipated travel delays and used the posted prices as indicators
37 of abnormal delays in traffic.

38 Fewer studies have explored the relationship between travel time unreliability and mode
39 choice. Nevertheless, Prashker (10) found that car users had less tolerance for waiting time
40 unreliability than transit users, suggesting that satisfaction of reliability is related to the modal
41 choice of individuals. Accordingly, Bhat and Sardesai (11) also recommended that travel time
42 reliability be included as an important performance measure of transportation services as it
43 significantly impacts the level of usage by commuters.

44 **How to Measure Travel Time Reliability?**

1 An abundance of research has emerged, providing an assortment of mathematical calculations to
2 calculate travel time reliability; however, there is no consensus within the transportation profession
3 as to what the appropriate measures should be (21; 30). Here, we briefly explain an example of a
4 simple measure that is most relevant to our study.

5 The buffer index is analogous to the concept of a “safety margin” presented by Knight (4),
6 referring to the extra time people add to their average travel duration to reduce the effects of
7 unexpected delays and to ensure prompt arrival at their destination. The buffer index is calculated
8 as the difference between the 95th percentile of travel time and the average (mean or median) travel
9 time, divided by the average travel time; it is conveyed as a percentage in which travel time
10 reliability decreases with higher values (30). For example, a buffer index of 30% would indicate
11 that the commuter should allocate 9 additional minutes for a 30-minute trip, whereas a buffer index
12 of 40% would indicate that an allocation of 12 additional minutes for travel is recommended.
13 Typically, these types of measures, which are mode specific, require day-to-day data in order in
14 capture the daily variations in travel time, and can be used to evaluate the effectiveness of policies
15 (30). For instance, Chen, Skabardonis and Varaiya (31) assessed the impacts of using real-time
16 information instead of historical data to alert drivers of traffic conditions at five locations on San
17 Diego freeways and found reductions of buffer time ranging from 7% to 31%.

18 Due to the data requirements, these measures are inappropriate for this study as each
19 observation in our dataset is a unique trip with a distinct origin and destination. However, since
20 our data is based on our respondents’ typical commute, we can assume that their behavior has been
21 adjusted according to their prior experience. Furthermore, although we cannot compute buffer
22 indexes for each network, we can compare the reported travel duration to the reported additional
23 budgeted time to determine the travel time reliability of the networks. To the authors’ knowledge,
24 no studies evaluating travel time reliability have measured additional budgeted time using
25 commuters’ revealed behavior, while comparing across modes.

27 **METHODOLOGY**

29 **Survey**

30 This study uses data from the 2013 McGill Commuter Survey, a university-wide travel survey.
31 The survey targeted students, staff and faculty and was administered online during March and
32 April 2013. In total, 20,851 members of the McGill University community were randomly selected
33 to partake in the survey and were sent invitation emails. Respondents had a period of thirty-five
34 days to complete the online survey, and prizes were offered as incentives for participation. The
35 response rate of the survey was 32%, which is comparable to earlier surveys conducted at North
36 American universities (32; 33). Incomplete and unreasonable responses were eliminated from the
37 database, leaving 5,599 records. In the survey, respondents recorded details about their typical
38 commute from their home location to McGill University for a cold and snowy day, and likewise
39 for a warm and dry day, answering questions regarding each aspect of their daily commute,
40 including duration, satisfaction with service quality, and mode. The respondents also reported their
41 socio-demographic information, travel preferences, and personal attitudes toward the commute
42 (34).

46 **Study Sample**

1 After removing additional records due to illogical responses (such as drivers without driver's
2 licenses), the final number of observations for the study sample is 2,496, comprising of 46%
3 students, 32% staff and 22% faculty, and a mode split of 16% drivers, 54% transit users, 6%
4 cyclists and 24% pedestrians. The final sample consists of respondents whose travel destination is
5 within McGill University's Downtown Campus, but does not include individuals travelling to
6 McGill University's suburban Macdonald Campus as the traffic patterns and levels of public transit
7 services available are very different.

8 In this study, drivers, cyclists, and pedestrians are single-mode users, while transit users
9 may have used multiple modes of transit (bus, metro or train), in addition to walking to and from
10 their transit stops. All respondents travelled directly from their home location to McGill University
11 without making any stops at other destinations such as to drop off their children or to purchase a
12 meal. The study sample does not include commuters who carpooled as car passengers or used the
13 private university shuttle bus, which offers transportation service between the two McGill
14 University campuses, due to the small number of observations. Travel duration is calculated using
15 the summation of reported times of all trip legs. This includes, for example, the time that an
16 individual spent waiting for his or her bus, as well as transferring from the bus to the metro. In
17 order to eliminate extreme travel times, the top 1% of reported travel duration for each mode was
18 removed.

19 The survey asked respondents to rate the importance of various home selection variables
20 with regard to choosing their current residence as well as the satisfaction with the modes they used.
21 To ensure that the impact of these variables can be evaluated appropriately, records of respondents
22 who did not provide an answer or stated that they had no opinion were removed. In the survey,
23 respondents also described details of their usual commute for two different weather conditions (a
24 cold snowy day and a warm and dry day). For each individual, we randomly selected one of these
25 conditions so that each individual is linked to only a single weather condition.

26 Table 1 presents summary statistics of the population sample by mode of transportation,
27 showing variables that will be tested across all models in the next section. A brief assessment of
28 the data reveals that 82% of drivers are McGill staff and faculty, resulting in an average age of 47
29 years and an average of 14 years at McGill. Pedestrians, on the other hand, are mostly students
30 (72%) and thereby have a lower average age of 30 years. Among the different groups of
31 commuters, pedestrians have spent the least number of years at McGill (mean of 5 years). As
32 expected, cyclists and pedestrians place the highest value on living in proximity to the university
33 and not having to drive.

34 The average commuters travel to McGill University about 18 days a month, equivalent to
35 four to five days per week. In general, these trips are not stressful (mean of 2.75 out of 5), nor do
36 they negatively impact punctuality (mean of 2.71 out of 5). Overall, commuters are satisfied with
37 the mode(s) they use (mean of 3.98 out of 5). Yet, cyclists are the only group that would like to
38 use their mode more (mean of 3.76 of 5), while drivers are the most inclined to feel that the only
39 good thing about travelling is reaching the destination (mean of 3.12 of 5).

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1 **TABLE 1: Summary Statistics – Mean of Variables**

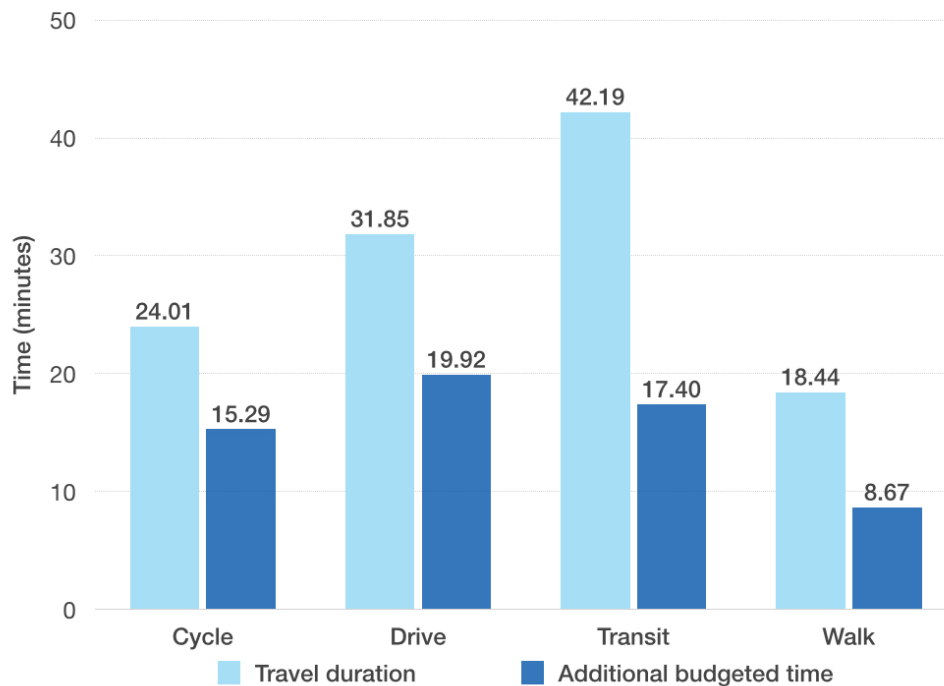
	General	Cycle	Drive	Transit	Walk
Sample size	2496	150	401	1352	593
PERSONAL CHARACTERISTICS					
Age	37.76	34.97	47.32	38.47	30.40
Female	0.58	0.51	0.49	0.61	0.58
Income (0-10)	1.74	1.75	3.35	1.58	1.02
Student	0.46	0.52	0.18	0.42	0.72
Staff	0.32	0.25	0.32	0.40	0.14
Faculty	0.22	0.23	0.50	0.18	0.14
Years at McGill	8.52	6.43	14.25	8.52	5.18
TRIP CHARACTERISTICS					
Warm, dry day	0.37	0.82	0.37	0.32	0.36
Stress (1–5)	2.75	2.05	3.00	2.83	2.59
Trip frequency (days per month)	18.00	18.19	14.89	17.87	20.39
TIME					
Duration (minutes)	33.80	24.01	31.85	42.19	18.44
Additional budgeted time (minutes)	15.29	10.01	19.92	17.40	8.67
My commute negatively impacts my punctuality (1–5)	2.71	1.77	2.66	2.91	2.53
MODE SATISFACTION					
Overall satisfaction (1–5)	3.98	3.96	3.86	3.93	4.18
The only good thing about travelling is arriving at my destination (1–5)	2.87	2.33	3.12	2.97	2.59
HOME SELECTION					
Importance of following factors in selecting current home:					
Proximity to McGill (1–5)	3.44	3.83	3.09	3.07	4.43
Proximity to transit (1–5)	4.09	4.33	3.47	4.36	3.85
Cost of commuting (1–5)	3.28	3.29	3.06	3.33	3.31
Not having to drive (1–5)	3.68	4.33	2.69	3.65	4.24
MODE					
Cycle	0.06	na	na	na	na
Drive	0.16	na	na	na	na
Transit	0.54	na	na	na	na
Walk	0.24	na	na	na	na
Would like to use this mode more (1–5)	2.43	3.76	2.21	2.09	3.03

na “not applicable”

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With regard to travel duration, pedestrians experience the shortest commute (mean of 18 minutes), and budget the least additional time (mean of 9 minutes). On the other hand, transit users travel the longest (mean of 42 minutes), and budget an average of 17 additional minutes of travel time for their commute, indicating a total travel time budget of 59 minutes. Drivers travel for an average of 32 minutes, but allocate the most additional time for their trips (mean of 20 minutes). Meanwhile, cyclists on average have a commute of 24 minutes, but budget 15 minutes extra.

1 However, if we try to estimate the buffer index by taking the amount of additional budgeted time
 2 as a percentage of average travel duration, cyclists are shown to have the least reliable network
 3 (64%). They are followed closely by drivers (63%), then pedestrians (47%), and lastly, transit
 4 users (41%). It is important to remember, however, that these percentages do not offer insight into
 5 the factors underlying these travel budgets. Accordingly the use of such index might not be the
 6 best way to compare network reliability of different modes. Figure 1 compares the average travel
 7 duration to the average additional budgeted time across all modes. A series of t-tests and chi-square
 8 tests confirm that there are statistically significant differences between additional budgeted times
 9 across modes.
 10



11
 12 **FIGURE 1: Average travel duration and additional budgeted time by travel mode.**

13 Method

14 This study develops five log-linear regression models (one general model and four mode-specific
 15 models) in order to investigate the relationship between how much extra travel time individuals
 16 budget for their commute and the different commuting characteristics. Based on the results of the
 17 Shapiro-Francia test, we rejected the hypothesis of data normality and used Tukey's ladder of
 18 powers to determine that a log-transformation of the dependent variable would most significantly
 19 improve normality conditions for modeling. Additionally, respondents within the top and bottom
 20 1% of reported additional budgeted time were discarded to further enhance data normality.

21 Based on the literature review, commuting stress and non-punctuality are included in the
 22 models below as consequences of travel time unreliability. Predictable variations due to
 23 seasonality are controlled for by using a dummy variable indicating weather condition, while trip
 24 frequency and years at McGill are used as proxies for familiarity with the commute. Travel
 25 duration, home selection and personal characteristic variables listed in Table 1 were tested across

1 the five models, but the final models retain only variables that were theoretically relevant and
2 statistically significant.

3 In the general model, dummy variables denote which mode the commuter used, while the
4 transit model contains additional variables indicating the number of buses, metros and trains the
5 individual took during the trip to account for the impacts of transfer times across modes. Overall
6 mode satisfaction was tested across all models but did not show statistical significance, except in
7 the general model. However, the four mode-specific models also include other variables pertaining
8 to the specific mode.

9

10 **RESULTS AND DISCUSSION**

11 Table 2 presents the results of the log-linear regression models, which predict how much time
12 contingency an individual provides for his or her commute. Since the factors are generally
13 consistent across all models, this section discusses the results of all of the models simultaneously
14 but emphasizes significances between the modes.

1 **TABLE 2: Log-Linear Regression Results for Additional Budgeted Time**

	General Coefficient (90% CI)	Cycle Coefficient (90% CI)	Drive Coefficient (90% CI)	Transit Coefficient (90% CI)	Walk Coefficient (90% CI)
PERSONAL CHARACTERISTICS					
Age (years * 10 ⁻¹)	0.05*** (0.02 – 0.07)	0.14** (0.04 – 0.23)	0.07** (0.01 – 0.12)	0.03* (0.01 – 0.06)	0.06* (-0.01 – 0.11)
Female	0.11*** (0.07 – 0.15)	0.21** (0.05 – 0.39)	0.13** (0.04 – 0.22)	0.08** (0.02 – 0.13)	0.11** (0.03 – 0.20)
Income (0-10)	-0.01* (-0.02 – -0.01)	–	-0.02** (-0.03 – -0.01)	-0.01 (-0.03 – 0.01)	–
Years at McGill (years * 10 ⁻¹)	-0.03* (-0.06 – -0.01)	-0.14* (-0.27 – -0.01)	-0.05* (-0.10 – -0.01)	-0.01 (-0.05 – 0.03)	-0.08* (-0.16 – -0.01)
TRIP CHARACTERISTICS					
Warm, dry day	-0.06** (-0.10 – -0.02)	-0.02 (-0.27 – 0.23)	0.03 (-0.07 – 0.12)	-0.11*** (-0.17 – -0.05)	-0.03 (-0.12 – 0.06)
Stress (1–5)	0.04*** (0.02 – 0.06)	0.03 (-0.05 – 0.11)	0.07** (0.02 – 0.12)	0.04** (0.01 – 0.07)	0.06** (0.02 – 0.10)
Trip frequency (% of days per month)	-0.11** (-0.20 – -0.02)	-0.05 (-0.41 – 0.30)	-0.04 (-0.20 – 0.13)	-0.14* (-0.27 – 0.02)	–
TIME					
Duration (minutes * 10 ⁻¹)	0.13*** (0.11 – 0.14)	0.26*** (0.19 – 0.34)	0.01*** (0.01 – 0.02)	0.09*** (0.07 – 0.11)	0.26*** (0.22 – 0.30)
My commute negatively impacts my punctuality (1–5)	0.06*** (0.04 – 0.08)	0.11** (0.03 – 0.20)	0.01 (-0.03 – 0.05)	0.05*** (0.02 – 0.08)	0.05** (0.01 – 0.09)
MODE SATISFACTION					
Overall satisfaction (1–5)	-0.05*** (-0.08 – -0.02)	–	–	–	–
Consistent travel time (1–5)	na	–	-0.06** (-0.10 – -0.02)	–	na
Reasonable waiting time (1–5)	na	na	na	-0.07*** (-0.10 – -0.05)	na

	General Coefficient (90% CI)	Cycle Coefficient (90% CI)	Drive Coefficient (90% CI)	Transit Coefficient (90% CI)	Walk Coefficient (90% CI)
HOME SELECTION					
Importance of following factors in selecting current home:					
Proximity to McGill (1–5)	–	0.10** (0.02 – 0.17)	–	–	-0.01 (-0.06 – 0.03)
Proximity to transit (1–5)	–	-0.13** (-0.24 – -0.03)	-0.05** (-0.10 – -0.01)	–	–
Cost of commuting (1–5)	–	–	0.06** (0.02 – 0.10)	0.03** (0.01 – 0.06)	–
Not having to drive (1–5)	-0.01 (0.03 – 0.01)	–	–	-0.05*** (-0.07 – -0.03)	–
MODE					
Cycle	-0.52*** (-0.62 – -0.41)	na	na	na	na
Transit	-0.27*** (-0.34 – -0.21)	na	na	na	na
Walk	-0.64*** (-0.72 – -0.57)	na	na	na	na
Compared to: Drive	v	na	na	na	na
Number of buses	na	na	na	0.13*** (0.07 – 0.19)	na
Number of metros	na	na	na	0.01 (-0.06 – 0.08)	na
Number of trains	na	na	na	-0.12* (-0.22 – -0.01)	na
Would like to use this mode more (1–5)	0.03*** (0.01 – 0.05)	0.09** (0.02 – 0.16)	0.03 (-0.02 – 0.08)	-0.01 (-0.03 – 0.02)	0.09*** (0.05 – 0.12)
Constant	2.18*** (1.98 – 2.36)	0.60 (-0.07 – 1.27)	2.12*** (1.61 – 2.43)	2.26*** (2.03 – 2.48)	0.77*** (0.47 – 1.06)
n	2496	150	401	1352	593
R ²	0.36	0.33	0.31	0.21	0.25
Adjusted R ²	0.35	0.27	0.29	0.20	0.23

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$, – “found to be insignificant and removed”, na “not applicable”, v “comparison variable”,

1 Travel mode is the greatest determinant of how much additional time an individual
2 allocates for his or her commute. The general model estimates that holding all else equal,
3 pedestrians, cyclists and transit users budget 64%, 52% and 27% less additional time respectively,
4 as compared to drivers. This suggests that active transportation networks have greater travel time
5 reliability than the street network for drivers. Looking more closely at the transit model, it is
6 apparent that there are great differences in reliability between the bus, metro and commuter train
7 networks. For each bus an individual takes, he or she is predicted to budget 13% more additional
8 time and for every metro line, 1%. On the other hand, for every commuter train an individual takes,
9 he or she is predicted to budget 12% less additional time. A possible interpretation of these figures
10 is a perception that the commuter train network in Montreal is reliable, while the bus network is
11 perceived to have frequent problems with consistency due to congestion or bus-bunching. Taken
12 together with the finding that drivers allocate the largest amount of time strongly suggests that
13 Montreal has a reliability issue with its street network as users who commute on the street network
14 allocate the highest amount of extra time compared to other modes. Potential strategies to improve
15 the reliability of the network could include the presence of exclusive bus lanes for buses as well
16 as HOT lanes for cars or schemes of congestion charging with variable costs to attenuate on-street
17 congestion, particularly at peak hours. All these strategies can help in reducing the uncertainty in
18 the network usage and lead to a decline in the buffer time, which drivers and bus users add to their
19 daily commute.

20 Travel duration has the second strongest influence on the amount of additional budgeted
21 time. Travel distance was tested in the models but due to its high correlation with travel duration
22 (Pearson's correlation coefficient = 0.73), only one of the two variables can be included. Since
23 travel duration proved to be a stronger determinant than travel distance in the models, travel
24 duration is used. The models predict an increase of 26%, 26%, 9% and 1% of extra buffer time for
25 every ten minutes in travel duration for pedestrians, cyclists, transit users and drivers, respectively.
26 The idea that pedestrians and cyclists would add the greatest percentage of additional budgeted
27 time per unit of travel duration, while drivers would add the least can seem counterintuitive.
28 However, this may signify that the design of the street network in Montreal is inefficient for
29 pedestrians and cyclists, more so than for motorized vehicles. For example, depending on the
30 location, the street network may offer more direct routes for drivers compared to cyclists and
31 pedestrians who may be required to make a detour. If so, further investigation is required to
32 understand the source of the network inefficiency for cyclists and pedestrians. Also, due to the
33 nature of these modes, trip duration is much shorter for pedestrians and cyclists compared to that
34 for drivers or transit users (as observed previously in Table 1 and Figure 1). Consequently, an
35 addition of one minute allotted by pedestrians or cyclists appears to be much more than an addition
36 of one minute allotted by drivers or transit users. Hence, further investigation is needed to better
37 understand the additional time added for these modes.

38 Commuters who reported stressful trips, and felt that their commutes negatively impact
39 their punctuality are also estimated to increase their additional budgeted time. Greater stress
40 increases the buffer time by 6%, 3%, 4% and 7% for pedestrians, cyclists, transit users and drivers,
41 respectively. On a related note, pedestrians, cyclists, and transit users who feel more prone to
42 tardiness because of his or her commute will add 5%, 11% and 5% and 1%, respectively. These
43 results show that while stress has similar effects on users of all modes, cyclists allocate
44 considerably more extra time for their commute if they feel disposed to being late. Interestingly,
45 those who enjoy travelling with a particular mode also allocate extra time in their commute. The
46 general model predicts an increase of 3% of additional budgeted time for those who would like to

1 use their mode more, while the models for pedestrians and cyclists predict an increase of 9%.
2 Although not statistically significant, the models also predict an increase of 3% in additional
3 budgeted time for drivers, while transit users are predicted to budget 1% less extra time. On the
4 other hand, the variable indicating that arriving at the destination is the only good thing about
5 travelling was found non-significant across all models. These results are important to note because
6 they indicate that travel time reliability is not the only consideration individuals have when
7 deciding on departure time, and reflects similar findings from other research. For example,
8 Manaugh and El-Geneidy (35) found that certain groups of pedestrians, such as those who are eco-
9 conscious and value being physically active, are much more satisfied with their commute despite
10 travelling longer distances than other pedestrians.

11 Factors that are estimated to reduce time contingency include greater trip frequency, more
12 years spent at McGill, good weather and increased mode satisfaction. The models indicate that
13 greater trip frequency (the number of times a person is on campus per month) would lead to a
14 reduction of additional budgeted time of 5%, 14% and 4% for cyclists, transit users and drivers.
15 Likewise, the models also indicate a reduction of buffer time by 8%, 14%, 1% and 5% for
16 pedestrians, cyclists, transit users and drivers for every 10 years spent at McGill. This implies that
17 familiarity with the commute allows individuals to decrease their buffer time, likely due to a better
18 understanding of the sources of variations in their trip, such as the magnitude of peak-hour
19 congestion and how long it takes to reach the bus stop. Increased familiarity of the commute may
20 also indirectly decrease the amount of additional budgeted time through the reduction of
21 commuting stress. Ory et al. (36) and Legrain, Eluru and El-Geneidy (37) proposed similar
22 explanations of commuters being able to cultivate stress-coping strategies as they become more
23 familiar with the commuting environment.

24 Good weather, in general, is shown to reduce additional budgeted time for a commute.
25 While the models predict a reduction in allocated extra time of 3% for pedestrians and 2% for
26 cyclists, the impact of good weather is most pronounced and only statistically significant for transit
27 users, predicting a decrease in buffer time by 11%. This could imply that among the different
28 transportation networks, the stability of the public transportation network is the most affected by
29 weather conditions. Surprisingly, weather does not have a significant impact on the additional
30 budgeted time for drivers, even though driving conditions during winter in Montreal are
31 notoriously harsh. In fact, the models estimate a 3% increase in additional budgeted time. This
32 could, however, be due to the intensity of road construction and thereby numerous road closures
33 that take place in Montreal during the warmer months of the year.

34 The models also estimate a decrease in time contingency due to increased mode
35 satisfaction; greater overall mode satisfaction is predicted to result in a 5% reduction in additional
36 budgeted time. More specifically, drivers are estimated to decrease additional budgeted time by
37 6% with higher satisfaction of travel time consistency, while public transit users decrease
38 additional budgeted time by 7% with increased satisfaction of waiting time. This suggests that
39 drivers are sensitive to unexpected network disruptions, while reasonable waiting time is important
40 to public transit users. These findings agree with those of Brownstone et al. (29) where they
41 suggested that drivers dislike unexpected congestion, and those of Prashker (10), who predicted
42 that transit users value out-of-vehicle travel time reliability more than in-vehicle travel time
43 reliability. While extended waiting times for the metro and commuter train network are typically
44 limited to system breakdowns and human-caused delays, prolonged waiting times for buses are
45 usually related to congestion on the street network. This is further evidence pointing to low travel
46 time reliability of the street network in Montreal.

1 Other mode-specific variables were tested but proved to be non-significant. These variables
2 include satisfaction of travel time, comfort, safety from traffic, and safety from crime for
3 pedestrians. For cyclists, the evaluated variables were satisfaction of travel time, consistency of
4 time, comfort, safety from traffic, safety from crime and quality of cycling infrastructure. For
5 drivers, satisfaction of travel time, comfort, safety from traffic, safety from crime and cost of
6 commuting were tested. Lastly, non-significant variables for transit users that were tested consisted
7 of satisfaction of travel time, consistency of time, comfort, safety from crime, cost of commuting,
8 time it takes to reach the bus stop/metro station/train station, reasonable waiting time as well as
9 the ease of understanding information regarding public transit services. While real-time
10 information can impact travel decisions (9; 29), a possible reason that the variable regarding
11 understandability of information was not significant in the model is because presently, real-time
12 information is limited to the metro network. Information about the bus network is disseminated
13 through static schedules, which are updated every few months. However, this may soon be
14 changing due to improved technology and access to smartphone applications.

15 Lastly, the models include control variables for variation between individuals. In terms of
16 personal characteristics, age, gender, income and status at McGill (faculty, staff or student) were
17 tested. However, status at McGill was insignificant across all modes and hence, dropped from the
18 models. For every 10 years of age, the models predict an increased allocation of extra time of 1%,
19 7%, 3% and 3% for pedestrians, cyclists, transit users and drivers respectively. Higher income,
20 meanwhile, is related to a decrease of buffer time by 1% for transit users and 2% for drivers. The
21 models also suggest that females add more extra time than men do. More specifically, female
22 pedestrians, cyclists, transit users, and drivers correspondingly add 12%, 23%, 8%, and 13% more
23 extra time compared to their male counterparts. This finding is expected as females generally have
24 higher risk aversion than males (38). A number of home selection variables were also tested in the
25 different models. According to the general model, those who valued not needing to drive budget
26 1% less extra buffer time. Pedestrians who valued living near the university campus allocate 1%
27 less additional time, whereas cyclists are predicted to budget 10% more. On the other hand, cyclists
28 who chose their current home based on its proximity to transit, budget 13% less additional time,
29 while drivers who did the same budget only 5% less extra time. Furthermore, drivers who selected
30 their home due to the cost of commuting allocate 6% more time, but transit users, only 3%. Finally,
31 transit users who valued not driving reduce their additional budgeted time by 5%. Although there
32 are variations in the magnitude of the impact of home self-selection variables, the general trend
33 observed is that living in proximity to transit and not having to drive reduce additional budgeted
34 time, while individuals concerned about the cost of commuting make a trade-off by increasing
35 their travel buffer time. It is uncertain, however, as to why being close to the university would
36 encourage cyclists to add extra time contingency and reduce that of pedestrians. Perhaps, the
37 perception of cyclists aligns more closely to drivers than to pedestrians; it is possible that the
38 difficulty of navigating around road construction and obstacles faced by cyclists outweighs the
39 advantage of being near the university, which pedestrians enjoy.

40

41 **LIMITATIONS**

42 This study investigates the relationship between the amount of additional budgeted time
43 individuals allocate for their commute and characteristics of the commute, with an underlying
44 assumption that arriving to work or school on time is desirable. Realistically, however, the
45 importance of being punctual differs among individuals and may be influenced by cultural norms.
46 Hence, future studies should take into account the attitudes of individuals towards the importance

1 of being punctual, as this will have a direct impact on how much extra time he or she decides to
2 budget for the commute. Another limitation of this study is the lack of variation in trip patterns.
3 Since no respondents in the study sample made any stops during their commute to McGill
4 University, we were unable to validate the effects of trip chaining on the amount of additional
5 budgeted time, a potential area of research. In addition, a weakness in this study is its lack of mode-
6 specific commuting attributes, apart from mode satisfaction. For instance, one would expect the
7 availability and price of parking to have an effect on how much extra time a driver allocates for
8 his commute (39).

10 CONCLUSION

11 In conclusion, the findings of this study reveal significant differences between additional budgeted
12 times across modes, and this is most likely due to the nature of the different transportation networks
13 and their respective travel time reliabilities. We find that, on average, pedestrians, cyclists, transit
14 users and drivers respectively allocate 9, 15, 17 and 20 additional minutes for their commute to
15 McGill University. These additional minutes are not a part of the actual trip duration; rather, they
16 are unnecessary time lost due to travel time unreliability. From the results of the regression models,
17 we determine that Montreal's street network has reliability issues, and that the city should consider
18 implementing strategies such as exclusive bus lanes, and variable cost congestion price charging
19 schemes to alleviate the uncertainty in travel time and improve the reliability of the network. The
20 regression results also indicate inefficiencies in the pedestrian and cycling networks, despite
21 having relatively high network reliabilities. Further investigation is required to determine the
22 source of inefficiency and how to improve the networks so that less time will be lost to unnecessary
23 travel time. Although the findings from this study are derived from a university survey, we expect
24 similar findings among other groups in the region or even around the world. Transport engineers
25 and planners have been working on reducing travel time for commuters across different modes to
26 avoid time lost due to the commute. Findings from this study can help these engineers and planners
27 in developing better policies and solutions that can reduce the amount of time lost by commuters
28 in the form of buffer time.

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