

## Article

# Application of Historical Comprehensive Multimodal Transportation Data for Testing the Commuting Time Paradox: Evidence from the Portland, OR Region

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**Abstract:** There have been numerous theoretical and empirical transportation studies contesting the stability of commuting time over time. The constant commuting time hypothesis posits that people adjust trip durations, shift across modes, and sort through locations, so that their average commuting time remains within a constant budget. There is a discrepancy between studies applying aggregate analysis and those using disaggregate analysis, and differences in data collection may have contributed to the varying conclusions reported in the literature. This study conducts both aggregate and disaggregate analyses with two travel surveys of the Portland region. We employ descriptive analysis and *t*-tests to compare the aggregate commuting times of two years and use regression models to explore factors affecting the disaggregate commuting time at the individual trip level to examine whether the stability of the commuting time remains after substantial changes in the transportation and land use systems. Our study indicates that the average commuting time, along with the average commuting distance, increased slightly, as the mode share shifted away from driving during the examined period. The growth in shares of non-driving modes, which are slower than driving, coupled with an increased travel distance, contributed to the small increase in the average commuting time. Our analysis also indicates that the average travel speed improved for transit riders as well as drivers, contradicting earlier research that claims that public transit investment has worsened the congestion in Portland.

**Keywords:** commuting time paradox; transportation and land use; mode share; travel time budget



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## 1. Introduction

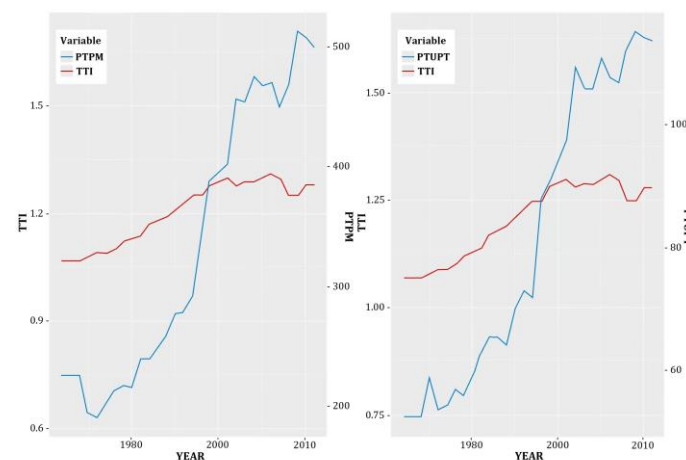
The “commuting time paradox” posits that the average commuting time remains constant across different time periods [1,2]. The stability of the commuting time has valuable practical implications for transportation planning and policy analysis, including transport improvements impact analysis, traffic congestion relief, mode shifting, and mitigating transport externalities. Numerous theoretical and empirical studies have focused on the stability of total travel time and commuting time [2–6]. The results of these empirical analyses are mixed: some studies suggest that the commuting time remains stable over time [2,4,5], while others have found contrary evidence [6–9].

Several issues potentially contribute to these mixed results. Firstly, the data collection methods may have changed over different periods within a study. For example, travel surveys have evolved from face-to-face retrospective interviews to prospective computer-assisted telephone interviews [10]. Additionally, there is a difference between activity diaries and travel diaries, which some argue might explain some, if not all, of the variations in the reported travel time expenditure across various studies [10].

Secondly, previous studies typically employed one of two categories of analysis: aggregate or disaggregate. Aggregate analyses use large geographic units, such as cities, states, nations, or population groups, whereas disaggregate methods analyze data at the household or individual level. While aggregate studies primarily utilize descriptive analysis techniques, disaggregate studies employ methodologies such as linear regression, structural equation modeling, and survival analysis [11–13]. These two types of studies often yield contradictory results: aggregate studies tend to show stability, whereas disaggregate studies fail to confirm this concept [10].

To determine if the average commuting time remains constant across different time periods, this study conducts both aggregate and disaggregate analyses of historical comprehensive multimodal transportation data. We use two travel surveys of the Portland region, conducted in 1994 and 2011, respectively. Seventeen years apart, these surveys were collected using the same method and an identical activity diary format. We employ descriptive analysis and *t*-tests to compare the aggregate commuting times of the two years and use regression models to explore factors affecting the disaggregate commuting time at the individual trip level after substantial changes to the transportation and land use systems in Portland, OR.

Another question of particular interest is the following: does the commuting time remain stable after the transportation and land use systems go through substantial changes like those in Portland, OR, between 1994 and 2011? The commuting time is subjected to significant transportation and land use changes, as well as significant demographic changes [14–16]. Between 1994 and 2011, the Portland region underwent significant changes to its land use and transportation systems. Households in the region grew from slightly fewer than 600,000 to more than 800,000, while employment declined slightly from 947,000 to 916,000. Expansion of the transit system nearly doubled the public transit passenger miles from 258.9 million to 499.3 million. As shown in Figure 1, the Travel Time Index (TTI), a measure of congestion, has increased drastically since the 1980s. The TTI is the ratio between the time taken to travel during peak hours and the time taken to complete the same journey at free flow [17]. Similarly, the Public Transit Passenger Miles (PTPMs) and Public Transit Unlinked Passenger Trips (PTUPTs) show a similar trend [17]. In particular, this study tests the “commuting paradox” [2,18] and “rational locator” [4] hypotheses. These hypotheses postulate that households and firms would adjust locations to maintain a tolerable commuting time. This aligns with the concept of the Travel Time Budget [10,11]. In addition to testing these hypotheses, regression models are employed to examine how socioeconomic and transportation characteristics affect the commuting time.



**Figure 1.** Travel Time Index, Public Transit Passenger Miles (PTPMs, in 1,000,000 s), and Unlinked Public Transit Passenger Trips (UPTPTs, in 1000 s) for Portland, 1982–2014 (data source: Texas Transportation Institute).

The remainder of this paper is organized into four sections. First, the literature on commuting time is reviewed. The second section presents the data and methodology used in this study. The third section presents the results of the descriptive analysis and regression analysis. The last section summarizes and discusses the results.

## 2. Literature Review

The “commuting time paradox” hypothesis suggests that the average commuting times tend to remain relatively constant across different time periods, despite changes in urban development, transportation infrastructure, and population dynamics. This phenomenon raises questions about the relationship between commuting behavior and urban growth, as well as the implications for urban planning and policy.

The commuting time paradox is examined through various theoretical frameworks. The Time Allocation Theory posits that individuals maintain a fixed amount of time for commuting, even as urban areas expand and living locations change, which results in stable commuting durations [19]. Behavioral Economics emphasizes the psychological aspects of commuting decisions, proposing that individuals adhere to a mental “travel time budget” that they are hesitant to exceed, further contributing to the stabilization of the average commuting times [20]. Together, these theories illustrate how various factors interplay to maintain consistent commuting durations despite changes in urban dynamics. The methodologies used to study the commuting time paradox hypothesis are diverse, encompassing quantitative, qualitative, and mixed-method approaches [10,11,18]. Quantitative methodologies are predominant in the study of the commuting time paradox, allowing researchers to analyze large datasets and identify trends over time. While aggregate studies primarily utilize descriptive analysis techniques, disaggregate studies employ methodologies such as linear regression, structural equation modeling, and survival analysis [11–13].

The studies inspired by Travel Time Budget (TTB) generally posit that the commuting time is stable. Purvis [5] used household travel surveys conducted in 1965, 1985, and 1990 to compare travel characteristics in the San Francisco Bay Area. The results showed that the average travel time per person per weekday increased from 52 min to 65 min between 1965 and 1981 but declined to 62 min in 1990 and that the average commuting time increased from 25.8 min in 1965 to 26.6 in 1981 and to 29.2 in 1990. Since the authors focused on testing the TTB hypothesis, they only examined the reasons for the change in total travel time, but did not investigate the factors influencing the commuting time. Levinson and Kumar [4] analyzed the travel time by mode and trip purpose with 1968 and 1988 household surveys in the Washington metropolitan region. The results showed that travel time and commuting time did not increase between 1968 and 1988, even though there was an increase in travel distance and commuting distance. They argued that this was caused by the “rational locator”, which meant that rational households and firms would adjust locations to maintain tolerable commuting time when they faced increasing traffic congestion and long travel distance. Furthermore, the commuting paradox has also been studied globally, and it was found that the average commuting time tends to remain constant across Europe, Asia, and Central America, even with urban expansion and enhanced public transport options [9,14,21,22].

Such aggregate studies generally support the concept of TTB [10,11,23] and concluded that the commuting time was also stable, but little work was done to investigate factors influencing the commuting time. In addition, most of these studies used household travel surveys conducted in different years, as the data collection methods evolved over time. Since there has been a marked transition in survey methodologies in the past decades [24], the difference in data collection of these surveys might affect the validity of these studies. For example, Levinson and Kumar [25] used the 1968 and 1988 household surveys in the Washington metropolitan region and found there was a marked increase in travel time for working people. The findings were prone to error, because there were differences in travel data collection between the two travel surveys, as non-motorized non-work trips were excluded in the 1968 travel survey while they were included in the 1988 travel survey [11].

Another line of studies focuses on changes in commuting time and factors explaining the changes. These studies are inspired by the urban spatial structure theory and attempt to investigate the impact of changes in urban structure on commuting time. On one hand, urban growth increases traffic congestion and commuting distance to the city center and thus leads to a rise in commuting time. On the other hand, the suburbanization of jobs and housing decreases the commuting distance, and traffic in suburban areas is not subject to traffic congestion.

Nationwide studies that used travel surveys in the early 1990s or before support the constant commuting time hypothesis. Gordon et al. [2] compared the auto commuting time between 1980 and 1985 in the largest twenty metropolitan areas. The results showed that the average auto commuting time decreased in eighteen of these twenty areas and kept constant in the remaining years between 1980 and 1985. The authors called this the “Commuting Paradox”, which meant that commuting did not increase given increasing traffic congestion because of location adjustment by households and firms. Hafeez [26] used Nationwide Personal Transportation Survey data to investigate the journey to work between 1977 and 1995. The results showed that the commuting time remained stable, because people adjusted their residential locations to maintain a reasonable commuting time, and the firms followed the labor force. These location adjustments yielded an apparent overall constant commuting time. They pointed out that location adjustment might be the cause for this phenomenon. Crane and Chatman [27] investigated the impact of employment decentralization on commuting time by industry in major U.S. metropolitan areas with individual-level panels between 1985 and 1997. They found that employment suburbanization led to a decrease in commuting time, and the effect of employment suburbanization on commuting time varied by industry type.

However, metropolitan studies, which also used travel surveys conducted in the early 1990s or before, indicate that there was an increase in commuting time. Clark and Kuijpers-Linde [7] examined the impact of urban spatial restructuring on commuting in Los Angeles metropolitan areas. They found that a polycentric urban form did not lead to a shorter commuting travel time and attributed the increase in commuting time to increased income and private vehicle dependence. Cervero and Wu [6] investigated the commuting time between 1980 and 1990 in the San Francisco Bay Area. The results showed that there was no association between a shorter commuting time and employment decentralization and sub-centering.

In the late 1990s, a marked increase in commuting time was also observed in nationwide studies [8]. The nationwide average commuting time increased by 2.2 min in the 1990s after excluding the increase resulting from data collection issues. Lee et al. [8] investigated the factors affecting the average commuting time. They found that demographic and transportation variables only explained a relatively small portion of the increase in commuting time and that a rise in income mainly contributed to the increase in the average commuting time.

To summarize, the nationwide studies that used travel surveys conducted in the early 1990s or before support the constant commuting time hypothesis, while the metropolitan studies that used travel surveys conducted during the same period found an increase in commuting time. This might indicate that the nationwide studies ignored the variation within metropolitan areas. However, a marked increase in commuting time was also observed by nationwide studies in the late 1990s. Thus, this study attempts to conduct a comprehensive case study with consistent survey data amid substantial changes in transportation and land use.

### 3. Data and Method

The data source for this study included two travel surveys: the 1994 Portland Activity Survey and the 2011 Oregon Household Activity Survey. These two surveys collected activity diaries of all members of the surveyed households during the survey period, as well as their socio-demographic characteristics. Table 1 presents a select subset of these variables

with descriptions and summary statistics. The 2011 survey involved 4799 households, 11,133 members, and 41,613 trips (in the Portland metropolitan area), while the 1994 survey included 4451 households, 10,048 members, and 129,188 linked trips. The 1994 survey covered two consecutive days, one of which had to be a weekday, while the 2011 survey was a 24 h weekday survey. To compare with the 2011 survey data, only trips made in one weekday were selected in the 1994 survey data. These two surveys both contain sampling weights that correct for the representativeness of each sample. This study used household weights to weight the travel outcome variables.

**Table 1.** Variables, description, and summary statistics.

Name	Description	Mean	Min	Max	%
TravelTime	Commuting time in minutes	24.70	1.00	119.00	
TripDist	Travel distance in miles	8.00	0.01	44.50	
Age65Plus	Older than 65: No				94.98
	Older than 65: Yes				5.02
VEH_OWEN	Vehicle ownership per HH: 0 vehicle				4.19
	Vehicle ownership per HH: 1 vehicle				27.22
	Vehicle ownership per HH: 2 vehicles				45.65
	Vehicle ownership per HH: 3 vehicles				14.90
	Vehicle ownership per HH: 4 vehicles				5.58
	Vehicle ownership per HH: 5 vehicles or more				2.46
Gender	Gender: Female				46.10
	Gender: Male				53.90
HHSIZE	Count of household members per HH	2.67	1.00	8.00	
HH_INC	Household income level: Poverty				4.34
	Household income level: DK/RF				5.25
	Household income level: lowInc				39.49
	Household income level: midInc				15.63
	Household income level: highInc				35.30
Year	Survey year: 1994				38.00
	Survey year: 2011				62.00
CBD	Whether the origin or the destination of a trip is located in the CBD area: Yes				11.70
	Whether the origin or the destination of a trip is located in the CBD area: No				88.30
Peak	Whether a trip is taken during peak period: Peak				68.00
	Whether a trip is taken during peak period: non-peak				32.00
Race	Household race: White				90.93
	Household race: Black				2.15
	Household race: Asian				1.06
	Household race: DK/RF				0.86
	Household race: Hispanic				2.47
	Household race: Native American				0.64
	Household race: Other				1.89

The unit of analysis for this study was the linked trip instead of the trip. The linked trip is defined according to activities (Survey Methods for Transport Planning [28]). For example, walking to a transit station, traveling in a transit vehicle, and walking from a transit station to the destination are three separate unlinked trips, which comprise a linked trip. A new linked trip takes place only when activity changes. This study focused on commuting trips or Home-Based Work (HBW) trips, which include both trips from home to work and vice versa. Finally, 10,366 HBW trips (3476 trips from the 1994 survey and 6890 trips from the 2011 survey) were selected.

For spatial analysis, the Portland metropolitan area was divided into two subareas: a CBD area that covered the Portland Downtown area and a non-CBD area. The CBD area is the regional center of employment, shopping, and recreation destinations and witnessed the most improvement in transit, biking, and walking infrastructure between 1994 and 2011. A CBD dummy variable was coded for HBW trips: if either the origin Traffic Analysis Zone (TAZ) or the destination TAZ of a trip was located inside the CBD area, the trip was coded as a CBD trip (CBD = 1), otherwise it was coded as a non-CBD trip (CBD = 0). There were 84.5% CBD trips and 15.1% non-CBD trips in the final dataset (Table 1).

We conducted both aggregate and disaggregate analyses on the 1994 and 2011 surveys. For the aggregate analysis, descriptive analysis and *t*-tests were conducted to test the constant commuting time hypothesis. For the disaggregate analysis, regression analysis was performed to examine how factors influenced the commuting time at the trip level. To avoid multicollinearity between independent variables, the Variance Inflation Factor (VIF) was calculated for the independent variables. Variables with a VIF larger than 5 were excluded in the regression analysis. Commuting time was the dependent variable in the regression model; it is a continuous variable and meets a normal distribution. Multiple linear regression models were estimated to examine how factors influenced the commuting time at the linked trip level. Multiple linear regression is a multivariate statistical technique to model the relationship between one dependent variable and two or more independent variables. The estimates of multiple linear regression models illustrate how the independent variables quantitatively influence the dependent variable. A violation of the ordinary least squares (OLS) assumptions was diagnosed, and the results indicate that the models are robust for valid inferences.

#### 4. Aggregate Analysis

The aggregate analysis indicated that the average commuting time, along with the average commuting distance, increased slightly from 1994 to 2011, as the mode share shifted away from driving.

##### 4.1. Mode Share

The commuting mode choice is a function of transportation supply, land use, and socioeconomic characteristics. Table 2 shows the mode share for the two years and its changes by area. For all HBW trips, the share of rail riders increased by 466.1%, which was likely attributed to the large extension of the light rail system during the period. The bus mode share saw a 63.3% increase. Driving was the only mode whose share decreased, and apparently shifted to other modes. There was a 77.8% increase in the mode share of passenger from a low base of 2.8%. The observed trends may suggest a potential increase in carpooling for commuting, but further investigation is required to confirm this hypothesis. The mode share of biking increased by 345.5%, which was likely attributed in part to the improvement in bike facilities throughout the region. Compared to the increase in biking, the increase in walking was low at 48.4%.

For the CBD commuters, the share of driving saw a larger decrease to 36.5%, along with a 24.39% decrease in the passenger share. This might result from the rise in parking costs during the period. The mode share of rail increased by 362.18%, to 19.1%. However, there was only a 5.55% increase in the bus mode share. It seems that commuters prefer the rail to the bus. In 2011, the combined mode share of rail and bus was more than 44%,



higher than the mode share of driving. The Portland case seems to show that investment in transit can reduce private vehicle dependence and that transit can be the dominant mode, at least for commuting trips to/from the CBD.

**Table 2.** Mode share for HBW trips by mode and area.

Mode	1994 All Trips	2011 All Trips	% Change	1994 CBD Trips	2011 CBD Trips	% Change	1994 Non-CBD Trips	2011 Non-CBD Trips	% Change
Driving	86.9	71.7	−17.5	55.8	36.5	−34.55	90.6	76.6	−15.4
Passenger	2.8	5.1	77.8	5.2	4.0	−24.39	2.6	5.2	103.3
Bus	4.2	6.9	63.3	24.1	25.4	5.55	1.9	4.3	127.4
Rail	0.8	4.7	466.1	4.1	19.1	362.18	0.5	2.7	503.8
Walk	3.9	5.8	48.1	8.3	5.1	−38.15	3.4	5.9	73.9
Bike	1.3	5.9	345.5	2.5	9.9	301.58	1.2	5.3	348.2

For the non-CBD commuters, the changes in mode share were as drastic, even though from a low base for most modes: the rail share increased from 0.5% to 2.7%, while the bus share increased by 127.4%, along with a 15.4% decrease in the driving share and a 103.3% increase in the passenger share.

#### 4.2. Income Group

In addition to analyzing the overall mode share, we thought it would be interesting to look into the mode share shift by household income and examine whether this shift happened evenly across income groups. Table 3 shows the mode share across income groups in 1994 and 2011. The growth rate of the transit mode share was higher for the poverty and low-income groups than for the middle- and high-income groups. For example, the mode share of bus increased from 4.81% to 19.15% for the poverty group, but only increased from 3.26 to 4.58% for the high-income group. This would seem to indicate that the poverty and low-income commuters were taking advantage of the transit investment, probably more than the middle- and high-income groups.

**Table 3.** Mode share for HBW trips by household income group.

Income Level	MODE	1994 Mode Share	2011 Mode Share
Poverty	PASSENGER	5.38	6.65
	BIKE	5.69	2.51
	BUS	4.81	19.15
	DRIVING	75.94	53.29
	RAIL	0.00	7.89
	WALK	8.18	10.50
Low income	PASSENGER	4.80	6.81
	BIKE	2.26	6.92
	BUS	6.64	7.40
	DRIVING	76.60	54.80
	RAIL	1.12	9.02
	WALK	8.58	15.06
Mid income	PASSENGER	2.71	5.64
	BIKE	0.99	5.40
	BUS	3.91	7.83
	DRIVING	88.99	72.70
	RAIL	0.83	3.73
	WALK	2.57	4.70
High income	PASSENGER	1.81	3.93
	BIKE	0.81	6.26
	BUS	3.26	4.58
	DRIVING	90.84	79.50
	RAIL	0.77	2.84
	WALK	2.51	2.90

#### 4.3. Commuting Time

Table 4 shows the weighted average commuting time by mode in 1994 and 2011. For all HBW trips, the weighted average travel time increased by 8.40%, from 22.8 min in 1994 to 24.8 min in 2011.

**Table 4.** Weighted average HBW trip travel time in minutes by mode and area.

Mode	1994 All Trips	2011 All Trips	Difference	% Change	1994 CBD Trips	2011 CBD Trips	Difference	% Change	1994 Non-CBD Trips	2011 Non-CBD Trips	Difference
Driving	22.0	22.6	0.6	2.65	24.9	26.3	1.4	5.90	21.8	22.3	0.5
Passenger	24.1	20.6	−3.5 **	−14.59	24.9	19.5	−5.4	−21.78	23.9	20.7	−3.2
Bus	42.0	41.6	−0.4	−0.11	38.2	36.4	−1.8	−4.78	47.7	46.6	−1.1
Rail	56.8	51.0	−5.8	−10.18	57.7	46.8	−10.9	−18.89	55.8	55.2	−0.6
Walk	11.7	12.6	0.9	7.43	16.5	20.9	4.4	26.69	10.3	11.5	1.2
Bike	26.6	25.8	−0.8	−2.99	29.5	28.3	−1.2	−4.06	25.9	25.1	−0.8
Overall	22.8	24.8	2.0 *	8.40	28.8	32.4	3.6 *	12.39	22.1	23.7	1.6 *

Notes: \* indicates  $p \leq 0.05$ ; \*\* indicates  $p \leq 0.0083$ .

The driving commuting time increased slightly, from 22.0 min to 22.6 min. The average bike commuting time decreased from 26.6 min in 1994 to 25.8 min in 2011. The extensive construction of bike infrastructure during this period may have contributed to the changes in the commuting patterns, although further research is needed to establish a direct link. There was a 7.43% increase in the average walking travel time. Compared with the 0.11% decrease in the average travel time of the bus commuters, the decrease in the average rail commuting time was much larger at 10.18%. The large decrease in rail trip travel time was likely due to the expansion of the light rail system.

For the CBD rail trips, the average commuting time decreased by 18.89% between 1994 and 2011, dropping from 57.7 min to 46.8 min, while there was a 1.05% decrease in the weighted average commuting time for the non-CBD rail trips.

In our analysis, we conducted the Shapiro–Wilk test to assess normality and Levene’s test to evaluate the homogeneity of variances, finding that both prerequisites for using a  $t$ -test were satisfied. The Shapiro–Wilk test indicated that the data for both groups followed a normal distribution, while Levene’s test confirmed that the variances were statistically similar. Consequently,  $t$ -tests were conducted to examine the differences in weighted average commuting time between 1994 and 2011. Table 4 shows the results of these  $t$ -tests. Bonferroni correction was applied for multiple comparisons (weighted  $t$ -test,  $p < 0.0083$ ). When considering the commuting trips by all modes, the travel time difference was significant (weighted  $t$ -test,  $p < 0.05$ ) for CBD and non-CBD trips. For the commuting time by individual mode, the travel time difference was only significant for all passenger trips.

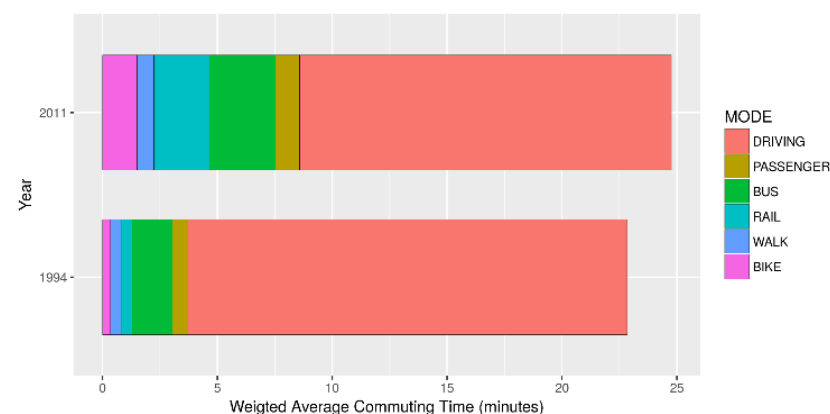
#### 4.4. Decomposing the Overall Commuting Time

As discussed above, the changes in overall commuting time were significant, but most changes in commuting time by mode were insignificant; so, we decomposed the overall commuting time. We calculated the average travel time of all linked trips by each mode and used the mode shares as the weights to calculate the weighted average travel time. For each survey, the sum of the weighted commuting time of each mode was equal to the overall commuting time. We used the mode share as a weight to aggregate the average commuting time, shown in Table 5. For the driving trips, the average commuting time weighted by mode share in 1994 was about 19 min; it was calculated by multiplying the average travel time of 22.0 min by the mode share of 86.9%. Though the average commuting time weighted by the mode share of the driving trips decreased, the average commuting time weighted by the mode share of the trips by all other modes increased. The bar plot (Figure 2) shows the changes between the two years.



**Table 5.** Commuting time and mode share.

Mode	1994 Average Travel Time	2011 Average Travel Time	1994 Mode Share (%)	2011 Mode Share (%)	1994 Travel Time Weighted by Mode Share	2011 Travel Time Weighted by Mode Share	% Change
Driving	22.0	22.6	86.9	71.7	19.109	16.182	−15.3
Passenger	24.1	20.6	2.8	5.1	0.687	1.043	51.9
Bus	42.0	41.9	4.2	6.9	1.766	2.881	63.1
Rail	56.8	51.0	0.8	4.7	0.475	2.417	408.5
Walk	11.7	12.6	3.9	5.8	0.454	0.724	59.4
Bike	26.6	25.8	1.3	5.9	0.350	1.513	332.1

**Figure 2.** Cumulative sum of average commuting time weighted by mode share.

#### 4.5. Commuting Distance

Commuting distance and time are closely related and are prevalent indicators for analyzing the travel behavior. In general, longer commuting distances tend to require longer commuting times. This part of the analysis aimed to analyze whether significant increases in commuting distances occurred over the study period and whether increases in commuting distances were responsible for increases in commuting times. This study used the route distance from the 1994 and 2011 surveys. This is more precise than the Euclidean distance, since it takes the roadway network into consideration. Table 6 compares the commuting distance by mode for 1994 and 2011. Because the walk and bike travel distances were imputed based on the travel time for the 1994 data, as their route distances were not recorded in the survey, they were not analyzed.

**Table 6.** Average commuting distance in miles by mode and area (in miles).

Mode	1994 All Trips	2011 All Trips	Difference	1994 CBD Trips	2011 CBD Trips	Difference	1994 Non-CBD Trips	2011 Non-CBD Trips	Difference
Driving	7.75	8.84	1.09 **	6.88	8.25	1.37	7.81	8.88	1.07
Passenger	7.38	6.93	−0.45	5.30	5.55	0.25	7.88	7.08	−0.80
Bus	6.67	7.17	0.50	6.27	6.28	0.01	7.26	7.92	0.66
Rail	9.03	11.52	2.49 *	7.96	10.70	2.74	10.18	12.32	2.14
Overall	7.70	8.74	1.04 *	6.67	8.09	1.42 *	7.81	8.83	1.02 *

Notes: \* indicates  $p \leq 0.05$ ; \*\* indicates  $p \leq 0.0125$ .

For all HBW trips, compared with the 8.40% increase in commuting time, the growth rate (13.09%) of travel distance was much greater. This seems to indicate that suburbanization led to an increase in travel distance, but the travel time did not grow in proportion because of the increase in speed. This was most remarkable for the rail trips. Though the average commuting time of the rail trips decreased by 10.18%, the travel distance increased by 27.55%. The travel distance of the CBD rail trips increased by 34.48%. The travel distance

of the CBD bus trips increased slightly. This revealed the commuters' preference for rail over bus for long trips. When bus and rail were both available, the commuters tended to choose the rail for long trips.

Table 6 also shows the results of the difference in means tests for commuting distance by mode and area. Bonferroni correction was used for multiple comparisons (weighted  $t$ -test,  $p < 0.0125$ ). When considering the commuting trips by all modes, the travel distance difference was significant (weighted  $t$ -test,  $p < 0.05$ ) for CBD and non-CBD trips. For the commuting distance by individual mode, the travel distance difference was only significant for the driving and rail trips.

#### 4.6. Trip Distribution

Figure 3 shows the percentage of commuting trip volume by area for 1994 and 2011. The proportion of CBD trips increased during the period between the two years. This seems to indicate that the importance of the CBD areas as an employment center strengthened from 1994 to 2011, which is different from the conclusion by Levinson and Kumar (1994). In their study, they found that the proportion of trips originating in or destined to the city center decreased from 1968 to 1988 in the Washington metropolitan area. A possible explanation for this discrepancy is a reverse of the suburbanization trend since the 1990s. The improvement in the transit network, particularly the light rail network, increased the accessibility of the CBD area and has likely contributed to the vitality of CBD as an employment, shopping, and recreation center.



Figure 3. HBW trip volume by area between 1994 and 2011.

#### 5. Disaggregate Analysis

The results of the descriptive analysis showed the changes in commuting trips between 1994 and 2011. Regression models were estimated to explore which factors influenced such changes. The commuting time was regressed on trip-related and socioeconomic characteristics. These variables were selected based on the existing literature [10,11]. Observations whose travel time, travel distance, and speed were above their 99% percentile values were excluded to eliminate potential outliers. Finally, we excluded 280 observations, i.e., 67 out of 3476 for the 1994 data and 213 out of 6890 for the 2011 data. Table 7 presents the full estimation results. The trip-related and socioeconomic characteristics explained a large portion of the variation in commuting time. The first column presents the results of the pooled model using data from both years. The second to fifth columns present the results for models segmented by year and area (CBD and non-CBD).

Table 7. Estimation results of regression models.

Variable	Pooled	1994 CBD	1994 Non-CBD	2011 CBD	2011 Non-CBD
ModeBike	−1.320 (0.995)	−6.280 (12.500)	−8.000 *** (2.830)	−3.830 (3.510)	−1.880 * (1.110)
ModeBus	14.700 *** (1.040)	11.900 *** (3.310)	13.900 *** (2.900)	6.830 *** (2.380)	20.500 *** (1.650)
ModePassenger	1.400 (0.980)	5.130 (5.310)	−2.510 (2.350)	−3.460 (7.670)	0.801 (1.120)
ModeRail	23.400 *** (1.560)	30.400 *** (7.530)	34.500 *** (10.700)	14.900 *** (2.900)	25.700 *** (2.200)
ModeWalk	−4.410 *** (0.769)	−9.160 ** (3.720)	−6.630 *** (1.380)	−11.600 (5.400)	−3.320 *** (0.988)
Age65Plus	0.714 * (0.423)	−7.880 (6.710)	−0.514 (0.848)	−0.419 (1.430)	0.793 (0.503)
VEH_OWN1	−1.340 ** (0.531)	1.020 (2.770)	−2.570 (1.650)	1.590 (1.500)	−0.852 (0.669)
VEH_OWN2	−1.020 * (0.564)	1.280 (2.940)	−2.060 (1.690)	2.300 (1.660)	−0.773 (0.715)
VEH_OWN3	−0.919 (0.607)	3.120 (3.290)	−1.510 (1.720)	1.270 (1.990)	−0.793 (0.769)
VEH_OWN4	−0.648 (0.684)	3.800 (4.200)	−1.460 (1.750)	5.490 * (2.880)	−0.229 (0.909)
VEH_OWN5+	0.012 (0.814)	13.500 (8.350)	−1.180 (1.930)	−3.230 (3.110)	1.070 (1.040)
GendMale	−0.124 (0.185)	−0.989 (1.060)	0.479 (0.309)	−0.458 (0.744)	−0.135 (0.243)
HHSIZE	−0.121 (0.077)	0.482 (0.436)	−0.192 (0.126)	0.033 (0.344)	−0.141 (0.102)
HH_INCDK/RF	−1.730 *** (0.611)			−4.230 * (2.420)	−1.350 * (0.696)
HH_INChighInc	−1.990 *** (0.496)	−1.960 (3.280)	−1.210 (0.928)	−6.050 *** (2.240)	−1.360 ** (0.616)
HH_INClowInc	−0.699 (0.510)	1.420 (3.460)	0.495 (0.959)	−6.700 *** (2.510)	0.178 (0.639)
HH_INCmidInc	−1.460 *** (0.489)	−1.650 (3.350)	−0.578 (0.926)	−4.920 ** (2.220)	−0.827 (0.601)
RaceAsian	1.530 ** (0.629)	5.310 (3.540)	1.340 (1.360)	−0.889 (2.180)	1.440 * (0.746)
RaceBlack	0.637 (0.896)	3.610 (5.020)	−0.088 (1.290)	−5.640 ** (2.450)	4.64 *** (1.540)
RaceDK/RF	−0.302 (0.987)		1.670 (4.100)	2.280 (2.450)	−1.080 (1.090)
RaceHispanic	3.650 *** (0.609)	10.500 ** (4.55)	0.938 (1.420)	2.320 (2.690)	4.320 *** (0.696)
RaceNativeAmerican	0.093 (1.140)	1.430 (10.300)	−1.370 (1.980)	−13.600 *** (5.130)	1.440 (1.390)
RaceOther	−0.621 (0.678)	−0.784 (4.640)	−1.980 (1.500)	5.940 ** (2.470)	0.747 (0.828)
Year2011	−1.440 *** (0.200)				
CBDYes	1.490 *** (0.313)				
ModeDriving:TripDist	1.520 *** (0.016)	1.860 *** (0.155)	1.800 *** (0.028)	1.120 *** (0.105)	1.400 *** (0.019)
ModeBIKE:TripDist	6.610 *** (0.227)	8.950 *** (1.790)	9.410 *** (0.740)	5.460 *** (0.861)	6.35 *** (0.243)
ModeBus:TripDist	2.420 *** (0.083)	2.410 *** (0.239)	3.370 *** (0.279)	2.110 *** (0.165)	2.100 *** (0.119)
ModePassenger:TripDist	1.690 *** (0.080)	2.870 *** (0.680)	2.430 *** (0.220)	2.200 *** (0.476)	1.540 *** (0.086)

Table 7. Cont.

Variable	Pooled	1994 CBD	1994 Non-CBD	2011 CBD	2011 Non-CBD
ModeRail:TripDist	1.730 *** (0.074)	0.959 ** (0.446)	1.600 ** (0.711)	1.500 *** (0.137)	1.800 *** (0.096)
ModeWalk:TripDist	20.800 *** (0.967)	31.000 *** (5.320)	32.200 *** (2.560)	20,900 *** (2.940)	18.500 *** (1.250)
ModeDriving:Peak	3.020 *** (0.223)	5.770 *** (1.620)	2.440 *** (0.332)	2.420 * (1.300)	2.960 *** (0.300)
ModeBike:Peak	1.930 * (0.991)	0.382 (11.000)	1.040 (2.880)	0.709 (2.960)	2.550 ** (1.140)
ModeBus:Peak	2.070 ** (0.976)	3.900 (2.650)	3.910 (2.480)	1.300 (1.920)	0.721 (1.560)
ModePassenger:Peak	0.609 (0.933)	−4.360 (4.670)	1.240 (1.910)	−5.710 (7.380)	1.240 (1.100)
ModeRail:Peak	0.482 (1.450)	14.600 * (7.480)	−2.020 (6.470)	−0.282 (2.370)	−1.640 (2.020)
ModeWalk:Peak	0.565 (0.824)	2.000 (3.730)	0.003 (1.671)	0.179 (4.110)	−0.276 (1.040)
Constant	12.600 *** (1.170)	11.700 * (6.540)	6.610 ** (2.870)	15.800 ** (7.920)	10.500 *** (1.350)
Observations	10,366	500	2976	1068	5.822
Adjusted R2	0.670	0.607	0.678	0.610	0.691

Note: \*  $p < 0.1$ ; \*\*  $p < 0.05$ ; \*\*\*  $p < 0.01$ . Std error in parentheses.

The mode dummy variables, with driving as the reference mode, showed the expected signs, and most of them were significant after controlling for socioeconomic and other trip-related characteristics. The significance of the mode dummy variable indicated that the commuting time of the target mode was significantly different from the travel time of the driving trips. In the pooled model, the dummy variables for bus, passenger, rail, and walk were significant, and their coefficients were positive, which means that the travel times of these modes were significantly longer than the driving time after controlling for other attributes. The long travel times of these modes coupled with their increased mode share contributed to the increased overall commuting time.

As expected, the coefficients of the interaction terms between mode and travel distance were all significant. The coefficients for these interaction terms were inversely related to the speed of a mode. For example, in the first column of Table 7, the coefficient for the driving–distance interaction term is 1.52, which means that it took 1.52 min to travel one mile by driving at an average speed of 39.5 miles/hour. In the segmented models, all coefficients for the interaction terms, except that between rail and travel distance, were larger in 1994 than in 2011. This indicates that the speed of all modes increased from 1994 to 2011 for both CBD and non-CBD trips, except for the rail mode.

The interaction term between driving and peak was significant in all models, while that between peak and other modes was not significant. This is because driving is more susceptible to congestion than the other modes. In the two CBD models, the coefficient for the interaction term between driving and peak was smaller in the 2011 model than in the 1994 model. This indicates that the peak congestion effect on driving was less severe in 2011 than in 1994. A possible explanation is that there were fewer commuting drivers, as some of them shifted to non-driving modes, as shown in the mode share section above. Interestingly, the peak effect was more severe in 2011 for the non-CBD trips, as the coefficient for the interaction term between driving and peak was larger in the 2011 non-CBD model than in the 1994 non-CBD model.

Among the socio-demographic variables, older age had a significant effect on the commuting time in the pooled model. Most dummy variables for car ownership were not significant, with the “no vehicle” category as the reference category. Gender was not associated with commuting time, which means that there was no difference in commuting time between males and females. The household size was found not to be associated with

the commuting time. The household income dummy variables were not significant in the 1994 CBD and non-CBD models. This means that there was no significant difference in HBW travel time between different household income groups. For the 2011 survey, the household income dummy variables, with poverty as the reference category, were significant in the CBD model, and only the dummy variable for the high household income was significant in the non-CBD model. Since all significant coefficients were negative, the commuters from low-income, middle-income, and high-income groups spent less time commuting than the commuters with a poverty status. This indicates that a higher income did not lead to an increase in commuting time, which is different from the finding of Clark and Kuijpers-Linde [7].

Some of the coefficients for race were significant, with White as the reference race. In the 1994 CBD model, the coefficient for Hispanic was significant and positive, meaning that Hispanics spent more time commuting than Whites. In the 2011 models, the effect of race on the commuting time was different between CBD and non-CBD trips. For the CBD trips, Black and Native American commuters spent less time commuting than White commuters. For the non-CBD trips, Asians, Blacks, and Hispanics spent more time commuting than Whites.

The CBD was associated with a longer travel time in the pooled model. The dummy variable for the year 2011 was significant and negative, which indicates that for the same trip, it took 1.44 min less in 2011 than in 1994, all else being equal.

The coefficients for the interaction term between mode and travel distance were converted to speed (miles/hour). Z tests were conducted to test the difference in travel speed. Table 8 shows the results of the Z tests, and the numbers in the table show the differences in speed.

**Table 8.** Z-test for the speed (mile/hour) difference by mode.

Mode	1994 CBD vs. 1994 Non-CBD	2011 CBD vs. 2011 Non-CBD	1994 CBD vs. 2011 CBD	1994 Non-CBD vs. 2011 Non-CBD
Driving	0.99	−10.64 *	21.17 *	20.18 *
Passenger	3.76	11.62	6.34	2.57 *
Bus	−7.14 *	0.17	3.46	10.60 *
Rail	−25.14	−6.62	−22.65	2.49
Walk	−0.08	0.37	0.93	1.00 *
Bike	−0.33	−1.55	4.29	4.62 *

Notes: \* indicates  $p \leq 0.05$ .

For the 1994 models, the speed difference between CBD and non-CBD bus trips was significant. It indicates that the speed of the CBD HBW bus trips was higher than that of the non-CBD HBW bus trips. This was consistent with our expectations, because bus services are denser and more frequent in the CBD area than outside of the CBD area. For the 2011 models, the speed difference between CBD and non-CBD driving trips was significant. For both the CBD and the non-CBD trips in 1994 and 2011, the speed difference between the driving trips was significant. This suggests that the driving speed increased, though there was increasing traffic congestion over the period. This is consistent with findings of Levinson and Kumar [4]. They argued that the overall speed increased from 1968 to 1988, though there was a common perception of worsening traffic congestion in the Washington metropolitan region, even as the transportation facilities improved.

## 6. Conclusions

The purpose of this study was to examine whether the commuting time is stable amid substantial changes to transportation and land use systems using the Portland, Oregon, region as a case study. We overcame two issues of previous studies by using consistent data and by combining aggregate and disaggregate analyses. The results of this study indicate that the commuting time increased and that there were large changes in mode share and travel distance from 1994 to 2011. Thus, the evidence from this study does not support the

constant commuting time hypothesis [2,4] or the TTB concept [11,29]. The results of this study suggest that the “commuting paradox” or “travel time budget” is now less influential than it used to be. Traditionally, these hypotheses posit that individuals tend to maintain a relatively constant travel time budget, meaning that as the commuting distances increase, people adjust their travel behavior to keep their overall commuting time stable. However, our research indicates that this trend may be shifting where the constraints of the travel time budget appear to be loosening. In addition, this study provides an additional in-depth understanding of the increased commuting and its influencing factors after decades of stability. The growth in the mode share of non-driving modes coupled with the longer average travel time of non-driving modes contributed to the increase in commuting time. The increase in the non-driving mode share was partially attributed to the improvement in the transit system, especially the expansion of the rail system. These results contradict previous research that claims that transit does not contribute to an increased commuting time because it only accounts for a very small proportion of commuting trips. Moreover, the evidence of the Portland case indicates that continuous investment in transit and bike infrastructure can help reduce private vehicle dependence and strengthen the role of the CBD as an employment center.

The commuting patterns are a function of many factors, including, but not limited to, socioeconomic characteristics, social norms, transportation systems, and built environment. Between 1994 and 2011, the Portland region went through substantial changes to its land use and transportation system, as well as experienced population and economic development. The differences in commuting patterns between 1994 and 2011 represent a composite change in travel behavior resulting from changes in socioeconomic characteristics, social norms, and transportation systems. Our analysis shows that trip-related and socioeconomic characteristics explain a large portion of the variation in commuting time. The effect of trip-related and socioeconomic characteristics on the commuting time was significantly different between 1994 and 2011. In addition, the results show that the overall speed increased during the period between the two years, though there was a common perception of worsening traffic congestion.

The results of our analysis provide empirical evidence for long-term commuting trends amid substantial changes to transportation and land use systems, which will help policymakers devise policies and optimize investments to improve transportation and land use systems. First, with the loosening of the travel time budget and constant commuting time hypotheses, it may be necessary to invest in transportation infrastructure that can accommodate longer commutes. This could involve expanding public transit options and improving road networks and connectivity between different modes of transportation to facilitate longer distance commuting and enhance the overall transit experience. Furthermore, urban planning policies should encourage mixed-use developments where people can live, work, and play nearby to reduce long commutes and improve their quality of life. Second, policymakers should adopt a long-term perspective in transportation and urban planning, recognizing that commuting behaviors may continue to evolve. This includes being open to revising existing theories and frameworks to better align with the current realities. Third, policymakers should invest in data collection and analysis to better understand the changing commuting behaviors. This can help identify trends and inform transportation planning, ensuring that policies are responsive to the needs of the commuters in a rapidly changing landscape.

Though this study provides an additional in-depth understanding of the increased commuting and its influencing factors after decades of stability, policymakers should consider the following issues when making decisions. While this study used linear regression to examine the relationship between trip-related and socioeconomic characteristics and commuting time, the dual influences of socioeconomic characteristics on commuting time were not considered. For example, income appeared to mediate the relationship between travel behavior and car ownership. Additionally, the “commuting paradox” can be associated with the ecological fallacy, particularly when inferences about individual



behavior are drawn from aggregate data. The “commuting paradox” assumes that all individuals behave similarly regarding their travel time allocation. This assumption can lead to the ecological fallacy, as it overlooks the diversity of commuting experiences. For instance, some individuals may prioritize shorter commutes due to personal preferences or constraints, while others may be willing to spend more time commuting for better job opportunities. If policymakers or researchers rely solely on aggregate data to inform transportation planning or policy decisions, they may misinterpret the needs and behaviors of specific demographic groups.

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