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Title: Implications of Distracted Driving on Driver Behavior in the Standing Queue of Dual Left-Turn Lanes: An Empirical Study.

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Driver distraction is a commonly observable phenomenon with a significant effect on the transportation network. Although the negative effects of driver distraction on safety are commonly studied, there has been little effort made to investigate the impacts of distraction on efficiency.

This study will examine driver behavior in standing queues at signalized intersection approaches with dual left-turn lanes, and determine what impacts distraction and several other independent variables have on the headways of the first five vehicles. Examining an empirical data set of headway measurements and distraction classifications for over 4000 individual vehicles in Oregon, Utah, and Kansas, linear regression methods will be used to create estimates of the effect of seven in-vehicle distraction classifications (cell phone use, eating or smoking, talking to passengers, manipulating the dashboard other distraction, undistracted, or could not determine). Results show that different distractions increase the median headways of drivers from 5% to 19% when compared to an

undistracted driver. The implications of these increased headways on start-up lost time and thus efficiency are then examined.

Implications of Distracted Driving on Driver Behavior in the Standing Queue of Dual Left-Turn Lanes: An Empirical Study

by
Patrick Stanley Marnell

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Head of the School of Civil and Construction Engineering

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I understand that my thesis will become part of the permanent collection of Oregon State University libraries. My signature below authorizes release of my thesis to any reader upon request.

Patrick Stanley Marnell, Author

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1. Introduction

To even the most casual observer of the transportation system driver distraction is a commonly observable phenomenon. A cursory observation will show drivers talking on cell phones, drinking coffee, talking with passengers, or reaching for objects in the back seat at an alarming rate. In fact, examining crash data from 1995 to 1999 only 48.6% of drivers involved in crashes were identified as attentive (Stutts et al. 2001). The effect that distracted drivers have on the transportation system is undeniable and has very real cost. In 2011, the National Highway Traffic Safety Administration reported 3,331 people killed and 387,000 people injured in motor vehicle crashes involving distracted drivers (NHTSA, 2013).

In response to the high frequency and danger of distracted driving, many studies by many authors have examined how distraction negatively affects safety; for example McCartt et al. reviewed approximately 125 studies just on the safety consequences of cell phone use (2006). In one highly publicized example, cell phone use was shown to be as detrimental to driver performance as drunkenness (Strayer et al. 2003). Yet, while there is a wide body of knowledge about how distraction affects safety and can lead to increased crash rates, there is relatively little knowledge about how distraction also affects the efficiency of the transportation system.

This study will examine driver behavior in standing queues at signalized intersections with dual left-turn lanes, and determine what impacts distraction and several other variables are having on the efficiency of these signalized intersections. To accomplish this, over 30 hours of video footage was analyzed and reduced to create a data set containing headway measurements and distraction classifications for over 4000 individual vehicles in Oregon, Utah, and Kansas. Linear regression methods will be used to create estimates of the effect of seven different distraction classifications, and from these estimates the impact of distraction on start-up lost time and efficiency will be examined.

This study will first define the traffic engineering terms and concepts necessary for the reader's understanding of the larger work. Then, the existing body of knowledge relevant to the topics of driver distraction and the dual left-turn lane intersections will be examined. Next, the methods used to collect and analyze the data will be explained in detail. Then, from this analysis the effects of driver distraction on headway will be identified, and the implications of these effects will be discussed. Finally, the need for future research on distraction and efficiency will be highlighted.

2. Literature Review

This literature review covers several topics that are vital to understanding how distractions affect driver behavior in standing queues at dual left-turn lanes. First it will be necessary to discuss some of the fundamentals of traffic engineering, flow theory, and queuing theory, and to define several terms. Second, it is important to examine the geometric and operational characteristics of the dual left-turn. Next, the driving task and the effects of driver inattention will be explored; and finally, the influence and frequency of different types of distractions on driver performance will be explored.

2.1 Traffic Engineering and Flow Theory Fundamentals

First it will be important to discuss several terms and concepts related to traffic engineering and traffic flow theory. This section is by no means comprehensive, but should serve to provide the reader a working knowledge of the terms being used through the rest of this document.

2.1.1 Headways

In seeking to examine the effects of distractions on driver behavior at dual left-turn lanes it makes sense to focus on the measurement of "headway".   There are two different types of basic headways, time and distance. In the context of this document, and many traffic engineering applications, the term headway will refer to the time headway, but it is important to understand the relationship between the two terms.

The *distance headway* is the length between common points on successive vehicles and is the reciprocal of density (Equation 1) (Wright and Dixon, 2004).

$$Distance\ Headway\ \left[\frac{feet}{vehicle}\right] = \frac{1}{Density\left[\frac{vehicle}{mile}\right]} \times 5280\ \frac{feet}{mile} \tag{1}$$

The *time headway* is the duration of time for a common point on successive vehicles to pass a fixed point and is the reciprocal of flow (Equation 2) (Wright and Dixon 2004, Koonce et al. 2008).

$$Time\ Headway\ \left[\frac{second}{vehicle}\right] = \frac{1}{Flow\left[\frac{vehicle}{hour}\right]} \times 3600\ \frac{second}{hour} \tag{2}$$

For example, imagine two cars traveling at 30 mph (44 feet/second). The front bumper of the lead car passes a speed limit sign. Then five seconds later the front bumper of the following car passes the speed limit sign. The time headway between these two cars is five seconds. Alternatively, if one measures the distance between these two cars, the distance, and therefore the distance headway, would be 220 feet (Figure 1).

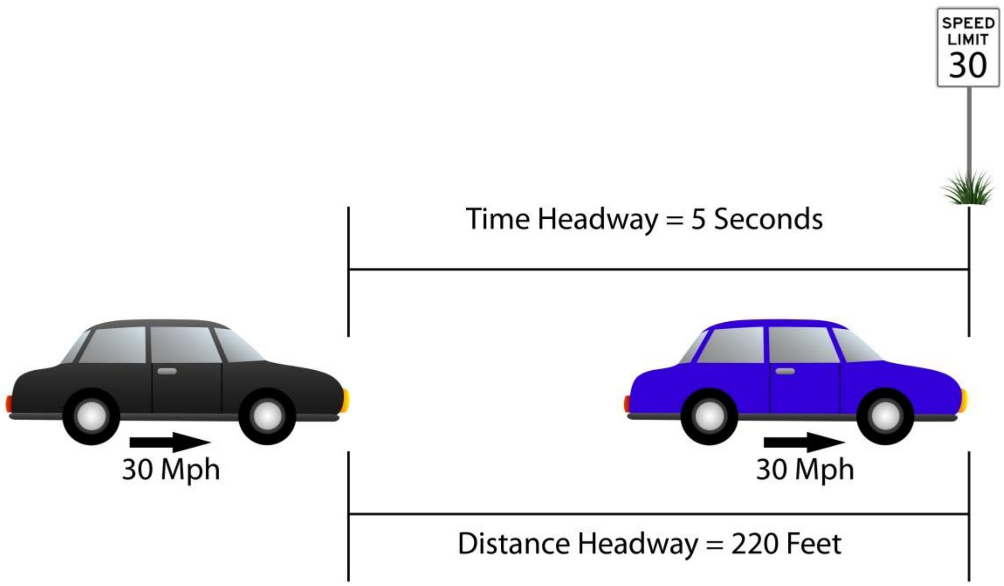


Figure 1: Time and Distance Headways

At signalized intersections a special case of headway exists. The first vehicle in a queue at a red light has no vehicle directly in front to measure headway from, so the headway of the first vehicle is defined as the time lapse between the activation of the green indication and the time when the front axle of the vehicle passes the stop line (Roess et al., 2011). The headway for subsequent queued vehicles is then measured normally using front axle as the common point on the vehicles and the stop line as the fixed object (Roess et al., 2011). A variety of factors can influence the headway of drivers; at a signalized intersection the perception-reaction time can be a critical factor.

2.1.2 Perception Reaction Time and Saturation Headway

When a driver is presented with new information, the driver must go through a perception-reaction process where they detect the event, process the information, make a decision about how to respond, and initiate the chosen reaction (Wright and Dixon, 2004, Roess et al., 2011). The time that this process takes is known as the perception-reaction time (PRT). For the purpose of engineering design, values of 1.0 and 2.5 seconds are used as estimations for PRT by ITE and AASHTO, respectively (ITE, 2010, AASHTO, 2011). However, it is important to note that PRTs are not fixed; they are a product of different human factors (HSM, 2010). For example, Johansson and Rumar found that when drivers had some expectation of needing to break, an urban environment for example, their mean break reaction time, a specific type of PRT, was 0.66 seconds (1971).

When a driver is stopped at signalized intersection in response to a red indication and subsequently a green indication is displayed, the driver will have some delay in his response because of the PRT (Roess et al., 2011). For this reason the first several headways in a queue are typically longer than the rest of the queue. After the fourth or fifth vehicle in a standing queue, the headway values will trend towards a relatively stable value known as the saturation headway (Koonce et al. 2008, Mannering 2009, Roess et al. 2011, HCM 2010). Figure 2 shows this relation between queue position and average headway.

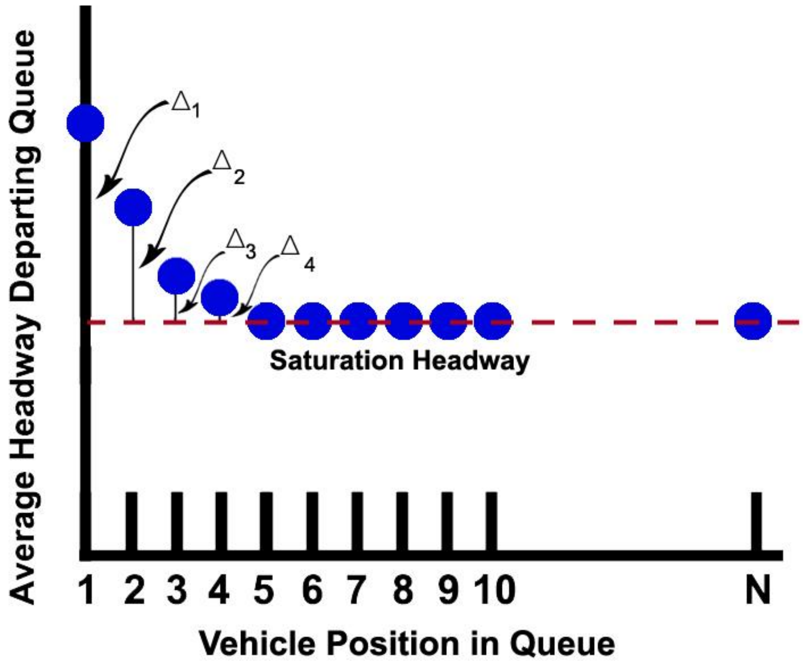


Figure 2: Headway by Vehicle Position in Queue (adapted from Roess et al. 2011)

2.1.3 Start-Up Lost Time

The sum of the extra time that drivers require over the saturation headway is known as the "start-up lost time" and is commonly estimated for engineering purposes at about two seconds (Koonce et al. 2008). The Traffic Signal Timing Manual defines start-up lost time as:

> *"The additional time, in seconds, consumed by the first few vehicles in a queue at a signalized intersection above and beyond the saturation headway due to the need to react to the initiation of the green phase and to accelerate to a steady flow condition." (Koonce et al. 2008).*

Mathematically start-up lost time is defined by Equation 3.

$$l = \sum_i \Delta_i \tag{3}$$

Where l = the start-up lost time
Δ_i = the incremental headway above the saturation headway (Figure 2)

Each time the green indication is displayed to a different movement at an intersection there will be some amount of start-up lost time. This will be true whether the green is displayed to a thru lane, a right turn lane, or a left-turn lane.

2.2 Left-turns and Left-turn Lanes

The left-turn is the most complicated and dangerous maneuvers at a standard intersection. Chang, et al. state “the presence of left-turning vehicles at signalized intersections tends to increase crash potential, causing excessive delay and reduction of intersection capacity” (1996). A standard four leg intersection contains 32 potential conflict points (Figure 3). Sixteen of the conflict points are considered crossing conflicts with the potential for greater crash severity. Of the 16 crossing conflicts points 12 are associated with left-turning maneuvers (Rodegerdts et al. 2004).

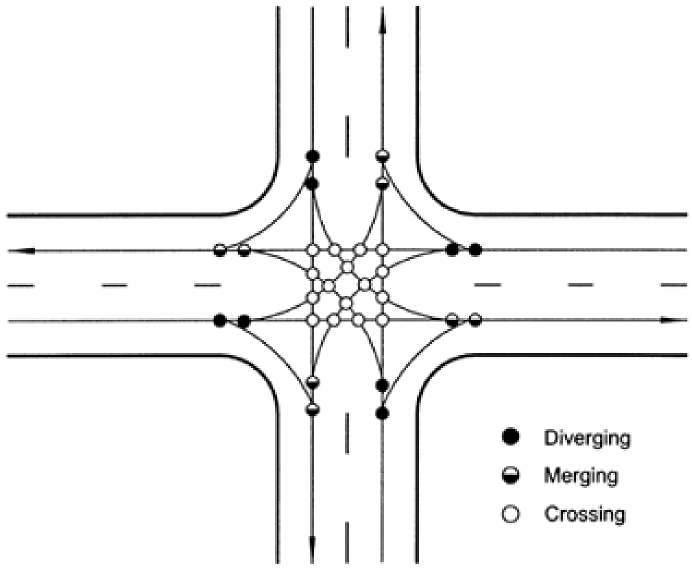


Figure 3: Intersection Conflict Points (Rodegerdts et al. 2004)

Left-turn lanes can be used to reduce the negative effects of left-turns. Maze, et al. state "the presence of a left-turn lane at a signalized intersection improves intersection safety and efficiency of operation" (2004). Additionally, the installation of a left-turn lane is expected to reduce red light running and rear end crashes (Rodegerdts et al. 2004).

Dual left-turn lanes describe two adjacent left-turn lanes serving one turning movement. Dual left-turns allow for higher volumes of left-turning vehicles from the same approach to use an intersection in a given period of time (Rodegerdts et al. 2004). One might expect that the use of dual turn lanes would double the capacity for left-turns, however in practice capacity is increased only by a factor of about 1.8 (Capelle and Pinnell 1961, Leisch 1967). Figure 4 shows an example of an intersection with a dual turn-lane.

Figure 4: Circle Blvd and Hwy 99 Dual Left-turn (adapted from Google Earth)

Stokes et al. examined saturation flows at dual left-turn lanes at 14 intersection approaches in Austin, College Station, and Huston, Texas. As part of their study they report mean headway values for each turn lane for queue position one through four individually, and for positions five and greater in aggregate (1986).

Table 1 show these values, with mean headways ranging from 2.4 seconds to 2.0 seconds. The mean headways from this experiment show the expect trend, as described in Figure 2, from higher to lower values as queue position increases.

Table 1: Average Left-Turn Departure Headways From Texas (adapted from Stokes et al. 1986)

Data Set and Lane	Sample Size	Mean Headway (second/vehicle)	Standard Deviation
All Vehicles			
Lane 1	1707	2.4	1.34
Lane 2	1751	2.4	1.29
$1 \le n_f \le n_{k(i)}$			
Lane 1	1500	2.3	0.81
Lane 2	1598	2.3	1.04
$2 \le n_f \le n_{k(i)}$			
Lane 1	1249	2.2	0.64
Lane 2	1347	2.2	0.98
$3 \le n_f \le n_{k(i)}$			
Lane 1	1000	2.1	0.60
Lane 2	1101	2.1	1.00
$4 \le n_f \le n_{k(i)}$			
Lane 1	752	2.0	0.58
Lane 2	859	2.1	1.09
$5 \le n_f \le n_{k(i)}$			
Lane 1	509	2.0	0.60
Lane 2	623	2.1	1.17

Shao and Wang studied the saturation flow rate from 1300 observations at six dual left-turn lanes Beijing, China (2011). Shao and Wang observed mean saturation headways ranging from 2.14 seconds to 2.74 seconds, and median saturation headway ranging from 2.00 to 2.39 seconds, depending on site location and lane (Table 2).

Table 2: Saturation Headways at Dual Left-Turns in Beijing, China (Adapted from Shao and Wang 2011)

Site	Location of the Lane	Sample Size	Mean Saturation Headway (sec)	Median Saturation Headway (sec)	Standard Deviation
1	Inside Lane	124	2.36	2.18	0.78
	Ouside Lane	101	2.14	2.00	0.37
2	Inside Lane	96	2.47	2.31	0.86
	Ouside Lane	129	2.41	2.30	0.55
3	Inside Lane	47	2.20	2.03	0.73
	Ouside Lane	141	2.24	2.17	0.60
4	Inside Lane	68	2.19	2.05	0.63
	Ouside Lane	38	2.25	2.25	0.28
5	Inside Lane	71	2.74	2.39	1.70
	Ouside Lane	86	2.30	2.10	0.52
6	Inside Lane	276	2.30	2.12	0.85
	Ouside Lane	139	2.44	2.37	0.70

From the work of Stokes et al. and Shao and Wang there is some evidence that the lanes in a dual left-turn configuration have slightly different flow characteristics. Although, it is difficult to see a consistent trend in the limited data available, the effect of left-turn lane position warrants further consideration.

2.3 The Driving Task

Having discussed several traffic engineering fundamentals, and the characteristics of the left- turn and left- turn lane, it will next be important to consider the driver and the driving task. The driving task can be disaggregated into three component parts: control, guidance, and navigation. These tasks are listed in order from the least to the most complex. Control consists of the most basic tasks of operating a vehicle such as steering and speed control (HSM 2010). Guidance encompasses more complicated tasks such as keeping the vehicle following a desired path down a road, or responding to traffic conditions (HSM 2010). Finally, navigation, the highest level task, includes route navigation and trip planning (HSM 2010). Any task that the driver is engaged in other than the control, navigation, or guidance task is a distraction from the driving task.

2.4 Driver Inattention

Driving a vehicle is a complicated divided attention task that inevitably involves multitasking. Even when focused entirely on the driving task, the driver must divide his attention between control, navigation, and guidance. The human brain does not perform multiple tasks particularly well (Dewar et al. 2007). When attempting two or more tasks simultaneously, even tasks that one is adroit at, the brain must split its resources resulting in a degraded ability to perform either task (Dewar et al. 2007, Regan et al. 2008). Simply put, when drivers attempt to perform multiple tasks they are more likely to miss cues critical to safety (National Safety Council 2010).

The National Safety Council describes inattention as "cognitive distraction” which “contributes to a withdrawal of attention from the visual scene, where all the information the driver sees is not processed" (National Safety Council, 2010). Klauer et al. expand on the topic defining “driver inattention” as: attending to secondary tasks, driver drowsiness, driving-related inattention to the forward roadway, and non-specific glances away from the roadway (2006). Klauer et al. found that the risk of a crash or a near crash increases when the driver’s eyes are diverted from the roadway for longer than two seconds (2006). Driving-related inattention to the forward roadway, such as checking the rearview mirrors, was classified as a “safety enhancing activity,” and was found to have a positive effect on safety in general. However, even a safety enhancing activity can increase the risk of a crash if the activity takes their eyes off the road for longer than two seconds (Klauer et al. 2006).

2.5 Driver Distraction

Driver distraction is a subset of driver inattention where the inattention is caused by an "explicit activity" (Regan et al. 2008). In other words distraction requires that the driver actually be engaged in an act such as eating, using a cell phone, or daydreaming, rather than just being drowsy or otherwise inattentive (Regan et al. 2008).

Commonly, distractions are described as manual, visual, or cognitive (NHTSA, 2010). A manual distraction occurs when a driver uses his hands (or feet) to perform a task other than driving. Reaching for an object in the back seat or manipulating a radio dial would fall under this category. Visual distraction occurs when a driver looks at something unrelated to the driving task. Examples of visual distractions include checking a text message, reading a billboard, or looking at a navigation system. Cognitive distractions occur when a driver's mental capacity is focused on a task, such as thinking about what to have for dinner, or daydreaming. Rarely do distractions fall neatly under a single category (NHTSA, 2010). For example, reading a text message might causes a manual distraction as the driver finds and manipulates the cell phone, a visual distraction as the driver reads the message, and a cognitive distraction as the driver processes the message.

The myriad of diver distractions can also be divided in other ways. Some choose to classify distractions as in-vehicle or outside of vehicle. Examining data from the years

1995-1999, Ranney reports that approximately 70% of distractions originate from within the vehicle, and 30% from outside the vehicle (2008). Others classify distraction by the complexity of the task. Klauer et al. describe simple, moderate and difficult secondary tasks that are performed during driving (Table 3)

Table 3: Examples of secondary task by difficulty (Klauer et al. 2006)

Simple Secondary Task	Moderate Secondary Task	Complex Secondary Task
1. Adjusting radio	1. Talking/listening to hand-held device	1. Dialing a hand-held device
2. Adjusting other devices integral to the vehicle	2. Hand-held device-other	2. Locating/reaching/ answering hand-held device
3. Talking to passenger in adjacent seat	3. Inserting/retrieving CD	3. Operating a PDA
4. Talking/Singing: No passenger present	4. Inserting/retrieving cassette	4. Viewing a PDA
5. Drinking	5. Reaching for object (not hand-held device)	5. Reading
6. Smoking	6. Combing or fixing hair	6. Animal/object in vehicle
7. Lost in Thought	7. Other personal hygiene	7. Reaching for a moving object
8. Other	8. Eating	8. Insect in vehicle
	9. Looking at external	9. Applying makeup

Another classification, for in-vehicle distractions at least, is to consider technology and non-technology based distractions. Technology based distractions include the use of cell phones, pagers, navigation systems, mp3 players, and various dashboard control distractions. Non-technology based distractions include tasks such as talking to passengers, eating, drinking, or smoking (Regan et al., 2008).

2.5.1 Eating, Drinking, and Smoking

Eating or drinking can involve multiple complex actions that divert driver attention from the road way for significant lengths of time. Similarly, smoking causes driver inattention and increases the risk of a crash or near-crash (Regan et al. 2008). In 2003, Glaze and Ellis preformed a pilot study examining 2,919 vehicle crashes in Virginia that involved distracted drivers. It was found that 6.3 percent of such crashes were related to eating, drinking, or smoking (Glaze & Ellis 2003).

2.5.2 Passengers

Another factor that can seriously affect driver performance is the presence of passengers. The effect of passengers on driver performance was first identified in 1940 by Lawshe. In a sample of 606 drivers it was found that drivers with passengers had a mean speed 2.1 mph lower than an unaccompanied driver. In 1983 Evans and Wasielewski showed that drivers maintain a larger headway when traveling with passengers. More recently

Simons-Morton showed that teen drivers maintained shorter headways with male passengers as opposed to female passengers or no passengers (2005). Additionally, studies have shown that younger drivers have a higher risk of being involved in a crash especially when accompanied by two or more young passengers (Regan et al. 2001). The extent to which the presence of passengers affects the drivers' behavior is a based on many factors such as driver experience, the age and gender of passengers and driver, the number of passengers, and the relationship of the passengers to the driver (Regan et al. 2001, Regan et al. 2008).

Although these studies do not directly isolate the effect of driver distraction from passengers, they highlight the effect that passengers can have on driver performance. The presence of a passenger can be a very real source of distraction to the driver, with distraction caused either by the behavior of the passenger or a conversation with a passenger.

2.5.3 Conversation and Cell Phone Use

Studies have also shown that having a conversation with a passenger can result in increased PRTs and reduced speeds (Strayer et al. 2003). However, whether the impacts of a conversation with a passenger in vehicle are the same as comparable to a cell phone conversation is unclear. Some findings support the idea that drivers will modulate their conversation to the driving environment and have less intensive conversation in high risk scenarios (Crundall et al. 2005, Regan et al. 2008). Others find no difference between a cell phone conversation and an in vehicle conversation (Laberge et al. 2004). While the exact effects of the cell phone on the distractive capacity of a conversation are unclear, what is clear is that the cell phone has greatly increased the ability of a driver to have a conversation while driving.

Drews et al. conducted research which found that using a cell phone while driving was more risky than many other distracting activities drivers currently engage in; however, drivers perceived conversing on a cell phone to be an acceptable risk (Drews et al. 2009). In 2006 Horrey and Wickens performed a meta-analysis of twenty three studies related to cell phone use while driving and found an increase in PRT of 0.13 seconds due to cell phone use.

Advanced cell phones or “smart phones” allow users to access the internet, play games, check email, and send text messages. Smart phones allow for a new level of multitasking and this has resulted in cell phone use as one of the main distractions that affect drivers (Edwards, 2001). Drews et al. classified text messaging while driving a “dual-task combination” with inherently high risk for the driver and other roadway users (2009). In fact, the risk of crashing while using a phone is estimated to be four times greater than the risk of crashing when not using a phone (McEvoy, et al. 2005).

Another area of interest about conversations and cell phones has to do with the use of hands free devices. Many states have introduced laws requiring that these devices be used for cell phone conversations while driving in an attempted to counter the negative effects of cell phone. As steps toward cell phone awareness these laws may be positive, but there is little evidence that a hands free device improves performance. Multiple studies show that the conversation is the major distraction, not the use of the hands (Consiglio et al. 2003, Patten et al. 2004, Strayer 2007). Horrey and Wickens' meta-analysis also concluded that hands free devices do not significantly reduce the effects of cell phone use while driving (2006).

The National Safety Council condemns these efforts saying "these laws give the false impression that using a hands-free phone is safe" when there is evidence that using a hands free device is no better than using a hand-held device (National Safety Council 2010, Consiglio et al. 2003). A University of Utah study compared the use of cell phones with drunk driving. This study compared the performance of cell phone drivers and drunk drivers to "baseline" or normal drivers and concluded that drivers using cell phones may exhibit greater impairments than legally intoxicated drivers (Strayer et al. 2003).

2.5.4 Dashboard Activates

While many distractions such as cell phones are brought into the vehicle, many distractions are designed as an integral part of the vehicle. Activities such as adjusting the vehicle stereo, adjusting the climate control, or using a GPS unit can be salient forms of distractions causing drivers to take their full attention off the road (Regan et al., 2008). In 2009 Horrey and Lesch preformed a study finding that not all drivers would allow these distractions to interfere with the driving task. However, the higher amount of concurrent activities the driver was trying to accomplish would provide a higher likelihood of the driver being distracted (Horrey and Lesch, 2009).

2.5 Frequency of Driver Distraction Types

Many different diver distractions have been documented in the literature including eating, drinking, holding a conversation, using a cell phone, or manipulating various dashboard controls. Stutts et al. examined the effect of driver distraction on crashes using data from 1995-1999 from the National Accident Sampling System Crashworthiness Data System (2001). Table 4 shows the proportions of specific distractions observed.

Table 4: Proportions Observed Distractions (Stutts et al. 2001)

Specific Distraction	% of Drivers
Outside person, object or event	29.4
Adjusting radio, cassette, CD	11.4
Other occupant in vehicle	10.9
Moving object in vehicle	4.3
Other device/object brought into vehicle	2.9
Adjusting vehicle/climate controls	2.8
Eating or drinking	1.7
Using/dialing cell phone	1.5
Smoking related	0.9
Other distraction	25.6
Unknown distraction	8.6
Total	100

Although these percentages have likely changed over the course of time, cell phone use has undoubtedly increased since 1999, this list servers to highlight many of the common distractions that drivers experience. Further, one should take special note of the implications that 25.6% of distractions that fall into the "other distraction" category. Over one quarter of the distractions Stutts et al. document are of types that represent less than 1% of the observed reactions highlighting the great diversity of distractions that drivers are commonly experiencing (2001).

2.6 Summary

In this literature review the fundamental concepts of headway and start-up lost time have been defined. The dual left-turn has been examined and empirical values of headways at dual left-turns have been identified. Further, the effects and frequency of driver distraction have been investigated.

While there is significant literature on the effects of distraction on safety, there is little on the effects of distraction on efficiency. Using headway and start-up lost time as efficiency measures, and isolating dual left-turn lanes as a specific lane configuration at signalized intersection approaches, this study will examine how distraction affects the efficiency of drivers discharging from standing queues in response to green indications at dual left-turn lanes.

To this end the effects on several different distractions will be examined. While a myriad of distractions exist spanning a variety of different classifications, this study will focus on in-vehicle distractions that can readily be identified from a visual inspection such as cell phone use, eating, smoking, talking to passengers, and manipulating dashboard controls. It is expected that these distractions will increase headways and start-up lost time, and that magnitude of the effect will vary between distractions.

3. Methods

This section will describe in detail the methods used to collect the data for this study. This study examines a dataset of observations from six field locations in three states collected during the summer of 2010. High definition video recording was used to create a rich dataset of observations of visibly distracted and undistracted drivers in dual left-turn lanes. This video data was subsequently reduced into measurements of headway and numeric classifications of distraction type.

3.1 Site Selection Criteria

This research effort involved collaboration between researches at Oregon State University (OSU), Utah State University (USU), and the University of Kansas (UK). Two experimental sites were selected in each of the hometowns of these universities Corvallis, Oregon, Logan, Utah, and Lawrence, Kansas. The experimental sites in each state were chosen by the local research team and were required to be intersections with at least one dual left- turn lane and with sufficient demand that queues of four to five vehicles would regularly accumulate in response to the solid red arrow indication. Additionally, it was required that video data could be collected in an inconspicuous manner. This prevented the presence of the research team from influencing the behavior of approaching drivers.

The following signalized intersection approaches were selected for inclusion in the study:

- Lawrence, Kansas
  - Iowa Street at 31st Street (SB and EB approaches)
  - Iowa Street at West 23rd Street / Clinton Parkway (SB approach)
- Corvallis, Oregon
  - NW Harrison Boulevard at Hwy 34 (WB approach)
  - NW Circle Boulevard at Hwy 99W (NB approach)
- Logan, Utah
  - 1400 N at Main Street (NB, SB, EB, and WB approaches)
  - 400 N at Main Street (NB and SB approaches)

Figure 5 show design drawings for the six intersections. At three of the intersections multiple dual left-turn approaches were observed. Although this increased the breadth of the study to 11 approaches, caution should be used in applying the results of the analysis too broadly. These intersections and approaches were not randomly selected and all of the study sites were located in relatively small cities in close proximity to large public universities. It is recommended that in future work the results of this study should be calibrated and validated against the local conditions before broad generalizations of driver behavior are made.

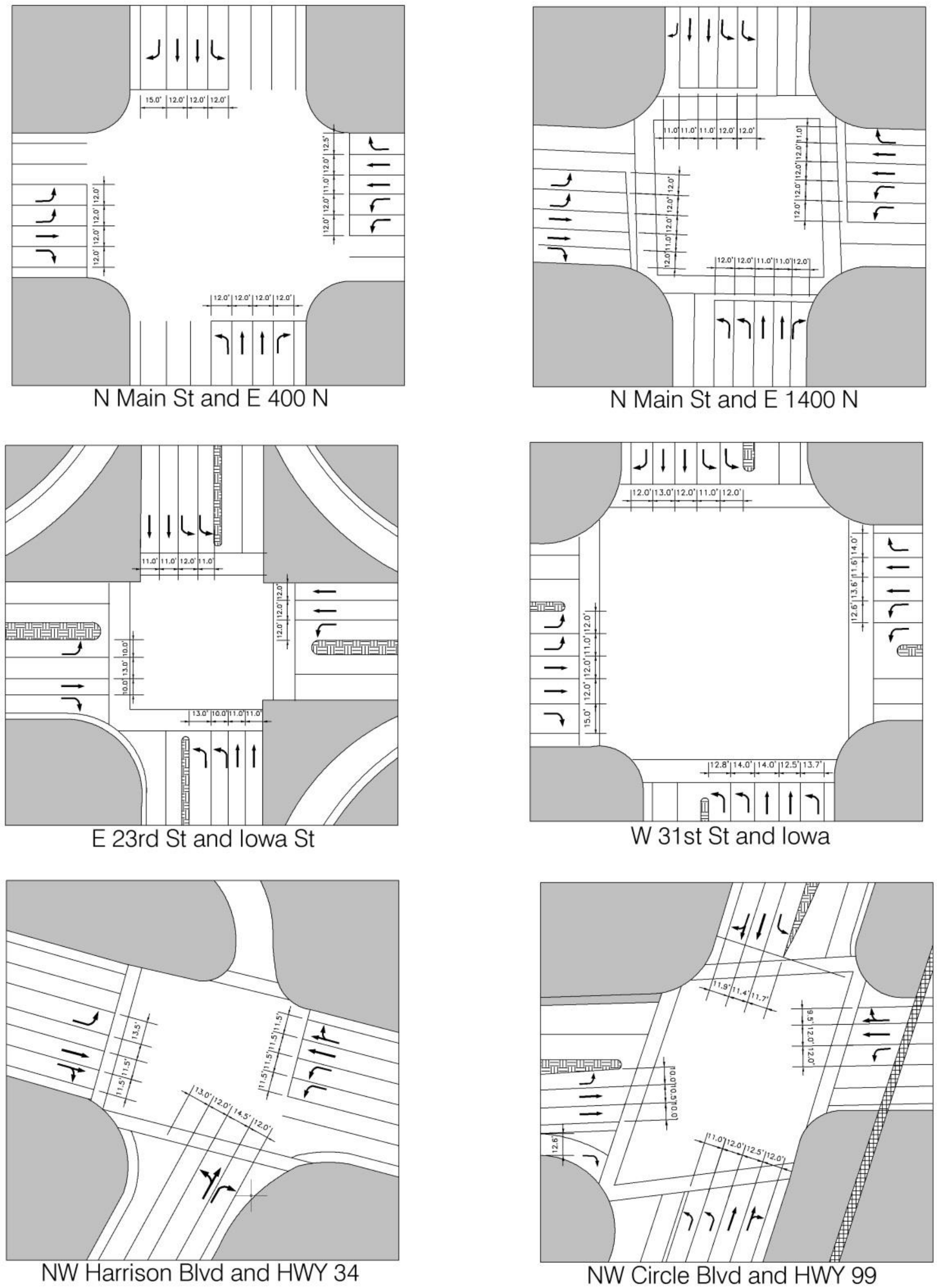


Figure 5: Design Drawings of Study Intersections

3.2 Video Data Collection

Data collection occurred in the summer of 2010 during daylight hours, on days with prevailingly good weather, and with dry pavement conditions. Data was collected on Tuesdays, Wednesdays and Thursdays in order to capture typical weekday travel conditions and driver behavior. To provide the largest possible data set in the available time, observations were made during periods where queuing was most likely to occur.

Researchers carefully positioned the camera equipment in the field so that the chance of being detected by the drivers under observation would be minimized. All of the field observations were recorded with high definition video cameras allowing researchers to identify precisely when the front axle of a vehicle crossed the stop line, and if a driver was distracted. Unfortunately, the video cameras were unable to record the signal that the queues responded to. A record of the signal timing was created by having a member of the research team observe the traffic signal and shout out the signal changes. This verbal information was recorded as part of the video footage.

While the video data collection provided a mechanism to observe drivers directly without influencing their behavior, it also posed some limitations for identifying certain types of distractions. Only in-vehicle distraction that could be identified visually were detected by this method be detected, and it is certain that some distractions were present that could not be detected through inspection of the video data.

3.3 Video Data Reduction

The video data was reduced by researchers on large high-definition LCD monitors at OSU. To maintain consistency among researchers reducing the data, a single transcription template was developed. This template contained detailed instructions on how the data was to be extracted and organized. To insure observer reliability at least two researchers transcribed an identical five minute section from each hour of video data. If any inconsistencies were detected, the entire hour was cross-checked by the researchers until the observations were in agreement.

Data was collected for each left-turning vehicle and driver in both the inside and outside left-turn lanes of the intersection approaches. Several types of data were tabulated for each individual vehicle and driver. These data included the left-turn lane occupied (inside or outside), position in the queue (1^{st}, 2^{nd}, 3^{rd}, 4^{th}, 5^{th}, 6^{th}, etc.), and type of distraction (cell phone, eating/smoking, talking to passengers, other, undistracted, or could not determine). Observed distractions were counted as a distraction only if the distracting activity tool place within 5 seconds of the onset of the solid green arrow indication.

The headway of vehicles was measured using the timestamp from the video footage when the front axle of vehicles crossed the stop line. Also, the time of the activation of the green arrow indication was measured using the audible record of the signal timing introduced by researchers in the field and the video timestamp. The video footage was recorded at a rate of 60 frames per second or one frame every 0.016 seconds; however, the timestamp of the footage displays values to the nearest 0.01 second. To address this discrepancy, the timing of events was rounded to the nearest 0.01 seconds as recorded by the time stamp. Figure 6 displays two still images of a vehicle observed in Oregon.

Activation of Protected LT Indication | Lead Vehicle Enters Intersection

Figure 6: Example of Video Data for Headway Calculation

The left panel of p shows a small pickup truck in the outside left-turn lane in the first position of a queue at the instant the left-turn green arrow was activated. The right panel shows the same pick-up when its front axle crosses the stop line 2.15 seconds after the activation of the left-turn green arrow. Since this vehicle was the first in the queue, the headway for this vehicle was calculated as the difference between the timestamp at the activation of the green arrow and the timestamp when its front axle crossed the stop line.

The headway for subsequent vehicles was then calculated as the difference in timestamps between the front axles of sequential vehicles crossing the stop line.

Table 5 shows a summary of the video data collected at each observed intersection approach and the resulting numbers of distracted and undistracted drivers. A total of 33 hours of video, representing 704 cycles, was recorded. For each state a minimum of 10 hours of footage was collected resulting in a total sample of 4,761 drivers. The statistical analysis of this data set is described in the following section.

Table 5: Summary of Video Data

City, State	Intersection Approach		Video (Hours)	Distracted Drivers	Undistracted Drivers	Unable to Determine
Corvallis, Oregon	Circle Blvd at 99W	(WB)	5	84	506	44
	Harrison Blvd at 34	(NB)	7	65	698	82
Logan, Utah	400 N at Main	(NB)	1.5	24	110	16
		(SB)	1.5	159	361	0
	1400 N at Main	(NB)	2	48	312	106
		(SB)	2	96	512	0
		(EB)	2	63	264	1
		(WB)	2	74	192	0
Lawrence, Kansas	Iowa at W 23rd St	(SB)	5	87	279	20
	Iowa at 31st St	(SB)	2	51	249	51
		(EB)	3	65	127	15
TOTALS:			33	816	3610	335

4. Analysis

This section will describe the statistical analysis of the data collected as described in the methods section. First, the basic data manipulation will be described, different data plots will be examined, and the normality of the data will be discussed. Next, a full model will be created, and several diagnostic tests will be performed. Finally, several reduced models will be created and compared to the full model to determine the best model to predict distracted and undistracted driver headways in standing queues at dual left-turn lanes.

4.1 Preliminary Visualization of Data

The tabulated data from the video footage was recorded in Microsoft Excel and then exported as a comma separated variable file (CSV). The CSV file was then imported into R Studio to perform the statistical analysis (R Core Team, 2012). Some additional data visualizations were produced with Microsoft Excel.

The headways observed were initially plotted against the queue position (Figure 7). A visual examination of the data appears to show the expected trend (Figure 2) where the headway values are initially high and begin to drop as queue position increases. As expected, when the queue position is greater than five a relatively stable average headway value is reached.

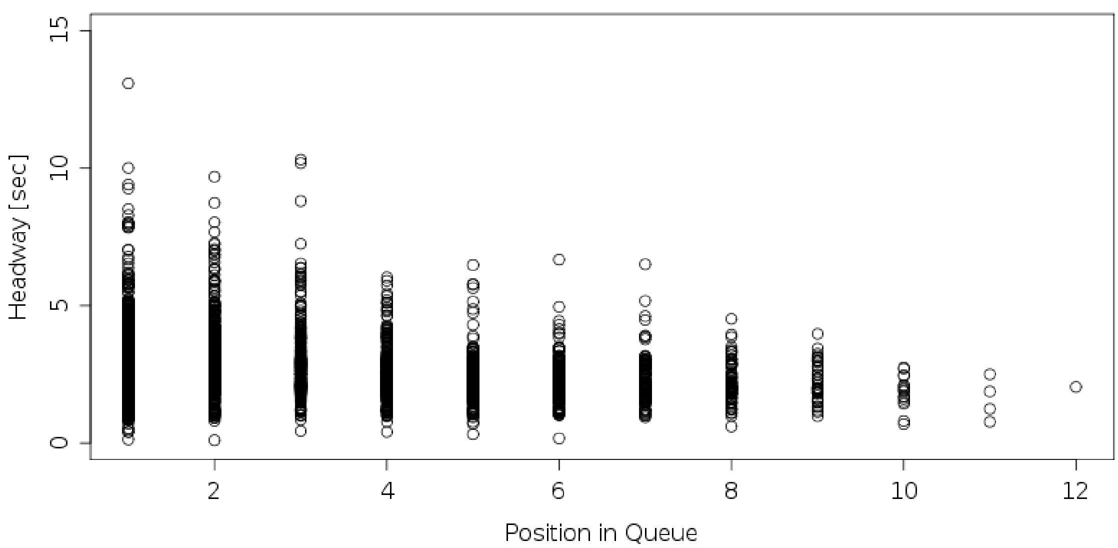
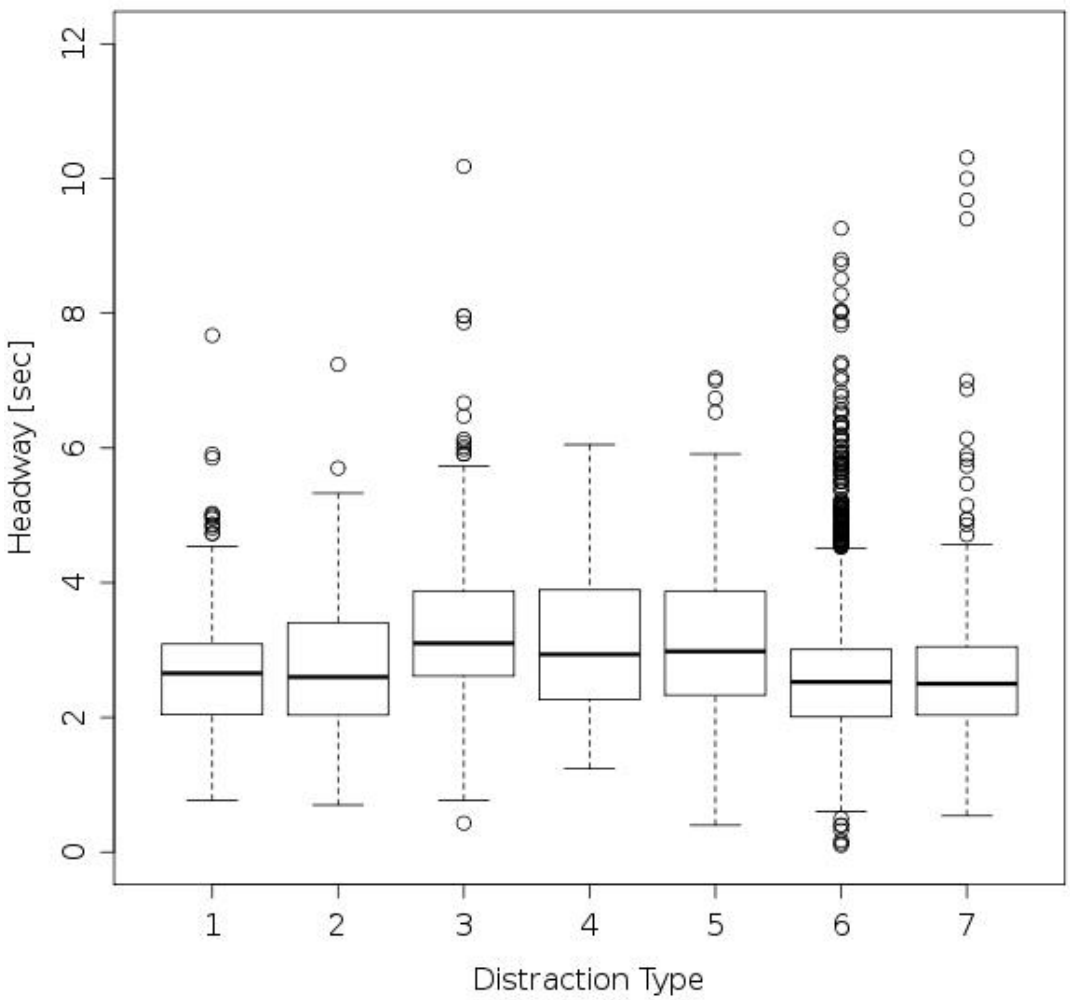


Figure 7: Raw Headways by Queue Position

Next a boxplot was created showing the mean headways by the different distraction types (Figure 8). This plot shows the mean headway for each distraction type as the thick black horizontal line in the middle of the box. The top and bottom edges of the boxes represent the upper and lower quartiles. Additionally, the upper and lower whiskers show the highest and lowest values not considered outliers. Finally, any points that are outliers are plotted as circles beyond the whiskers. A visual inspection of this plot showed that the headways of drivers with various distraction types have different mean values all ranging between two and three seconds. There are several points that are outliers, but considering the size of the data set not an alarming amount. In particular the "undistracted" driver shows many outliers. This may be due to the fact that as defined for this study the "undistracted" driver is only undistracted by visually identifiable in-vehicle distractions. These drivers could still be distracted by something happing outside of the vehicle, something that could not be detected through visual inspection, or just generally inattentive.



Distraction Type 1 = Cell Phone Use
Distraction Type 2 = Eating or Smoking
Distraction Type 3 = Talking
Distraction Type 4 = Manipulating Dashboard
Distraction Type 5 = Other
Distraction Type 6 = Undistracted
Distraction Type 7 = Unable to Determine

Figure 8: Box Plot of Headway by Distraction

4.2 Proportions of Driver Distraction

Next, pie charts of the proportions of distraction types were created. Figure 9 through Figure 12 are pie charts for the aggregate data, and each state individually.

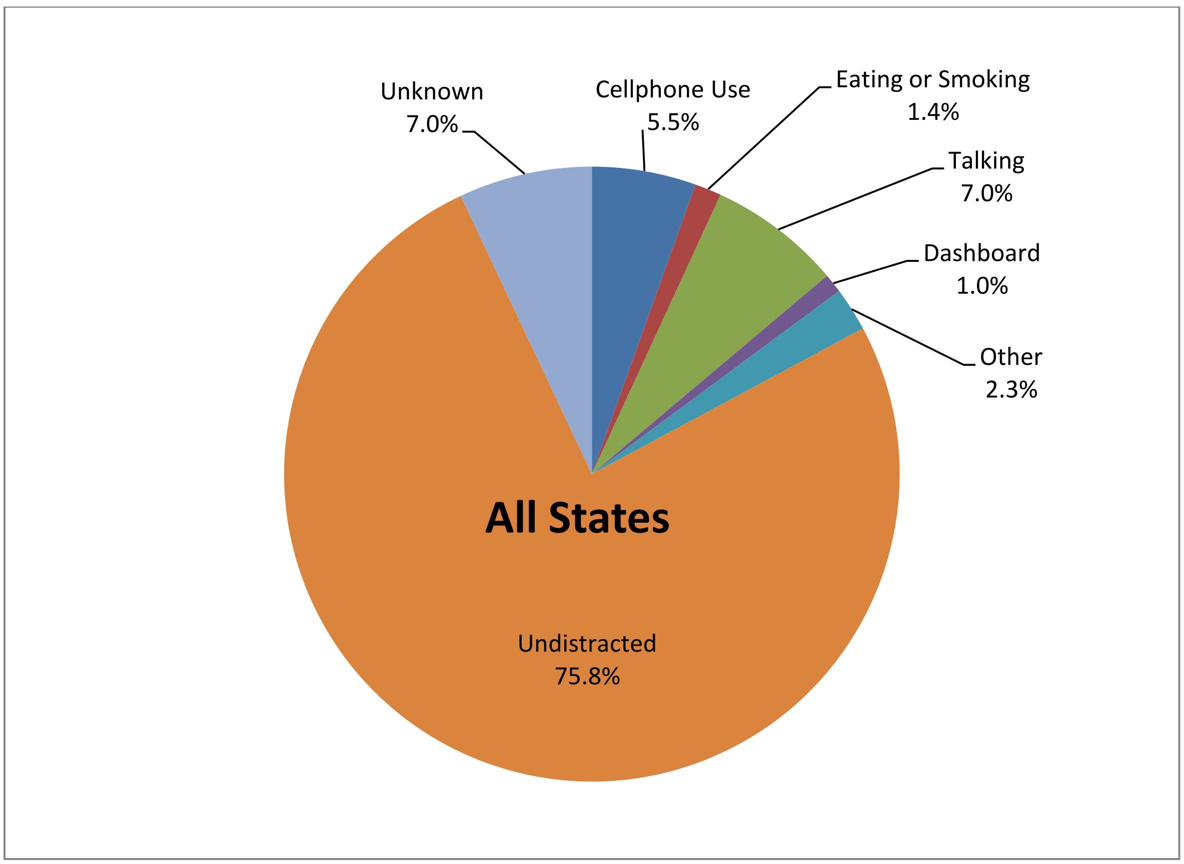


Figure 9: Distraction Proportions for All States

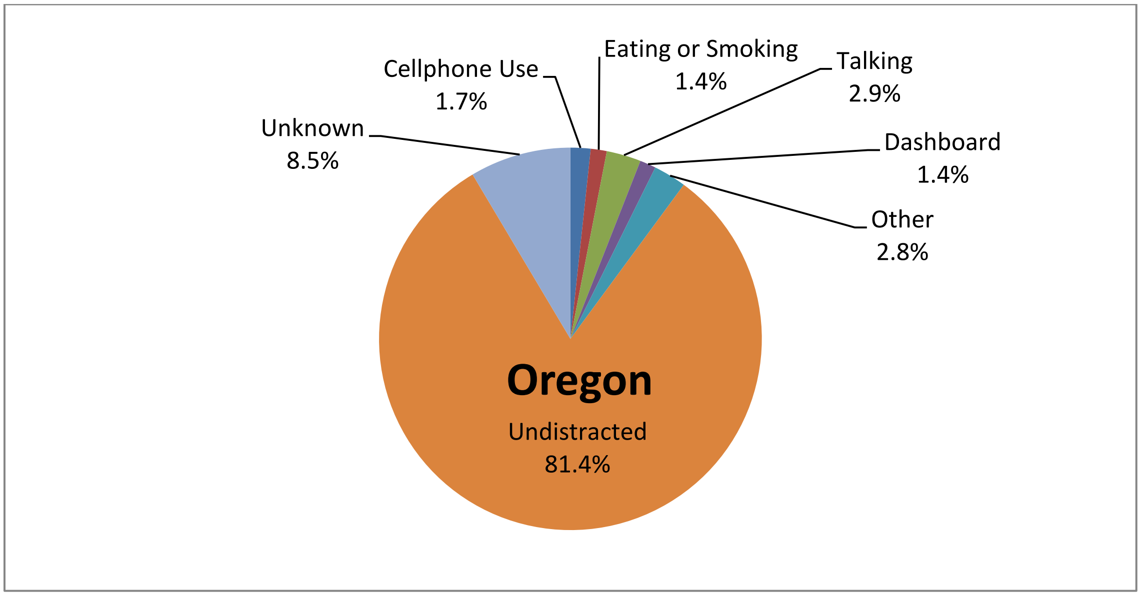


Figure 10: Distraction Proportions for Oregon

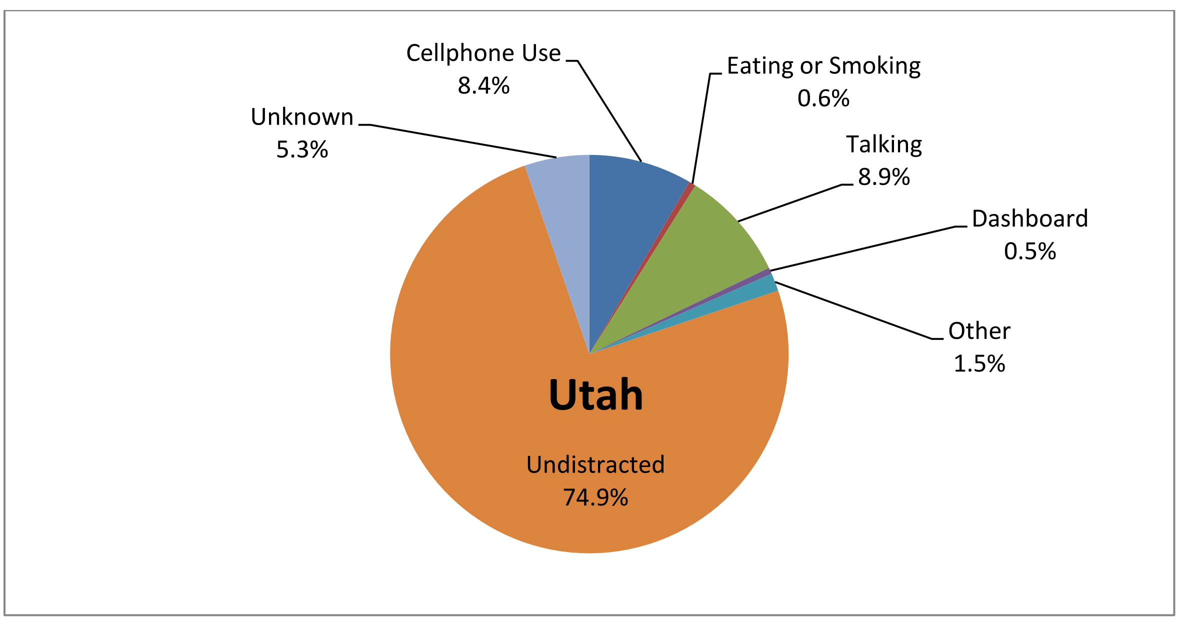


Figure 11: Distraction Proportions for Utah

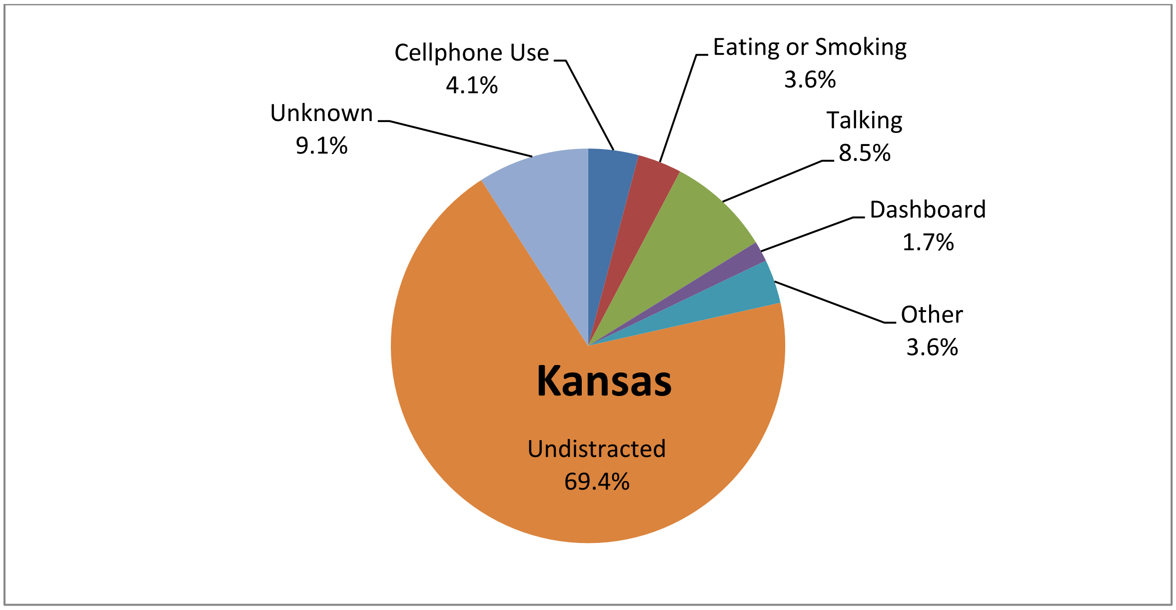


Figure 12: Distraction Proportions for Kansas

Then, a proportion test, using Pearson's chi-squared statistic, was performed comparing the proportion of distracted drivers vs. undistracted drivers between the three states.

The null hypothesis of this test is:

$$H_0: \textit{The three states have the same true proportion of distracted driving}$$

The proportion test found strong evidence ($p<0.001$) to reject this null hypothesis indicating that at least one of the states has a different proportion of distracted drivers.

4.3 Assessing Normality

Next, the data was examined to see if it fit a normal distribution. The data was plotted in a histogram (Figure 13). From this histogram, it can be seen that the headway data does not exactly follow the normal distribution and is shifted towards zero. This is almost certainly due to the fact that the values of headway are naturally low at signalized intersections, and by definition a negative value of headway cannot exist. This causes a skewing of the data toward zero.

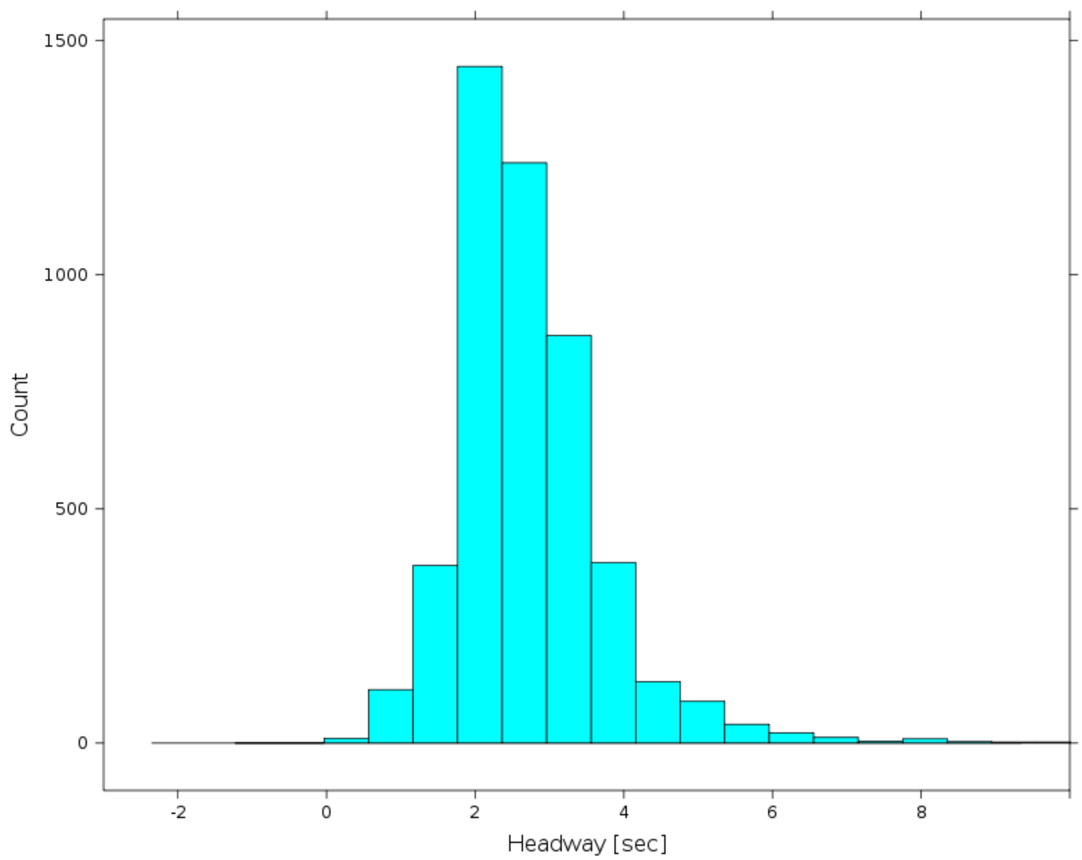


Figure 13: Histogram of All Headway Data

A natural log transformation of the headway values was performed to address the normality of the data. A histogram of the log transformed headways showed better consistency with a normal distribution (Figure 14).

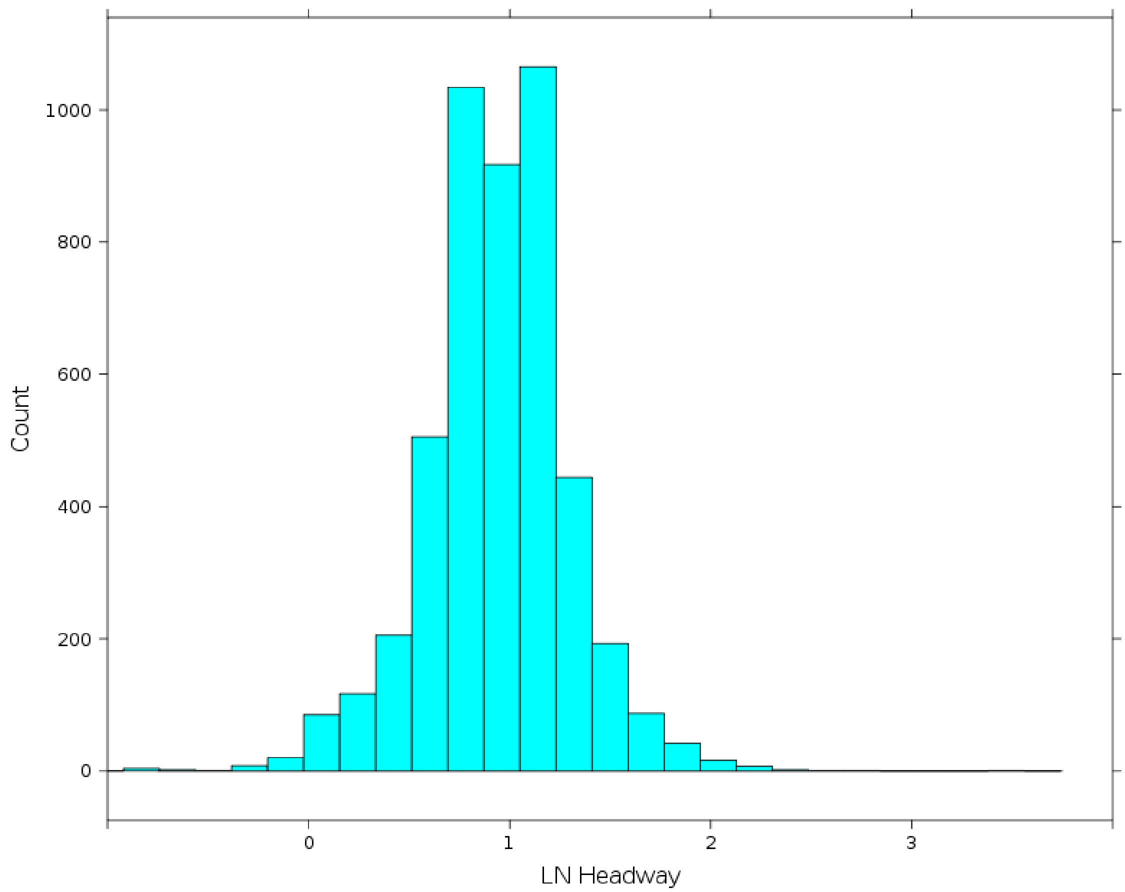


Figure 14: Histogram of Natural Log of All Headway Data

It is generally accepted that vehicles will reached the saturation after the fourth of fifth vehicle (Koonce et al. 2008, Mannering 2009, Roess et al. 2011, HCM 2010). For this reason only the headways of the first five vehicles were analyzed to determine the effects of distraction on headways and start-up lost time at dual left-turn lanes. A reduced data set was created containing only data from these vehicles. Although queues of up to twelve vehicles were observed, very long queues occurred relatively infrequently. The removal of these data only reduced the number of observations from 4761 to 4197, a delta of approximately 12 percent.

Figure 15 show the histograms for the reduced headway data and Figure 16 shows the log transformed histogram of the reduced data set. Again, the log transformation increases the normality of the data set.

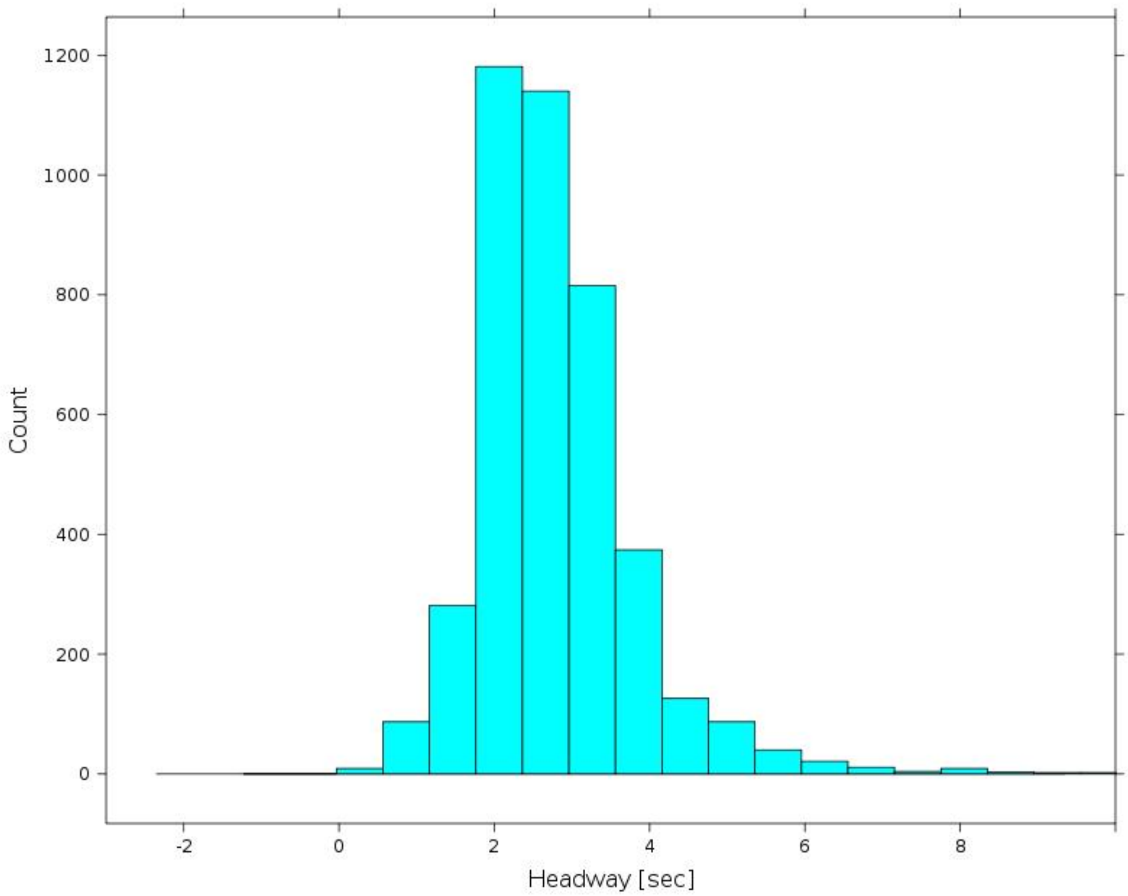


Figure 15: **Histograms of Headway Data for Queue Positions 1-5**

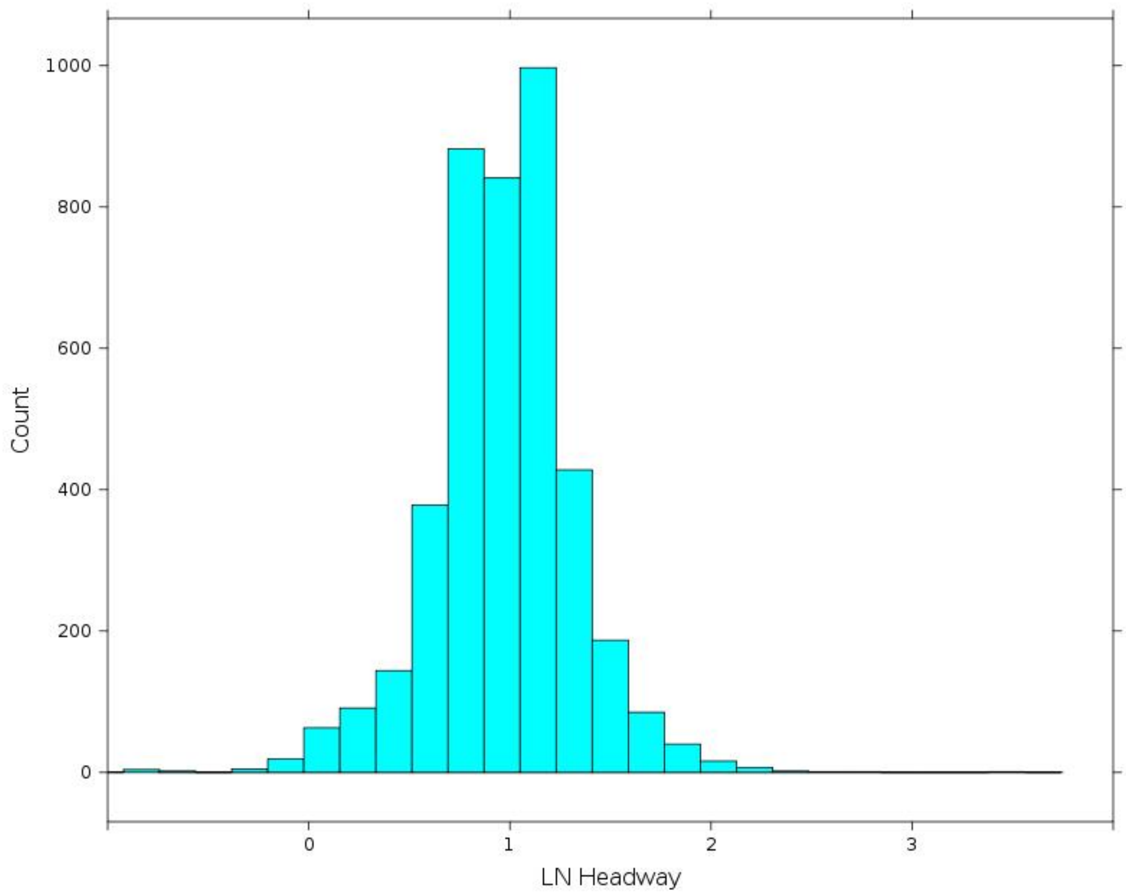


Figure 16: Histograms of Natural Log of Headway Data

Because the log transformed headway data conformed better to the normal distribution, the linear models were created using the transformed headway data. This will cause the results of the linear regression models to predict the median headways rather than the mean headways, and will also provide a more statically rigorous examination of the data.

4.4 Full Linear Regression Model

Once the log transformation of headway was selected as the appropriate manipulation of the data for regression analysis, a linear model was created. However, first it was necessary to decide what independent variables should be included in the full model.

From the literature, there is a clear consensus that the queue position will affect driver headways (Koonce et al. 2008, Mannering 2009, Roess et al. 2011, HCM 2010). Likewise, the literature suggests that there may be a difference in headway between the two lanes (inside and outside) of a dual left-turn (Stokes et al. 1986, Shao and Wang 2011). These variables, queue and lane position, were included in the full model. Additionally, a test of proportions of distracted drivers showed that one or more of the states had a different proportion of distracted drivers (see section 2.5). It was thought that this could be a significant factor on the headway, so state was also included as a variable in the full model. Finally, the effect of distraction on driver behavior was the central topic under investigation, so the distraction type was included as an independent variable as well.

A full linear regression model was created including these four independent variables. Because the independent variables are a set of discrete characteristics, not continuous values, dummy variables were created. For the full model, dummy variables were assigned to each of the seven distraction types, the five queue positions, the three states, and the two left-turn lane choices. This also made it necessary to set a reference level for each independent variable. The undistracted driver, in queue position one, in Kansas, in the inside turn lane was used as the reference level. These variables will not appear in the full regression model, but rather their effects will be accounted for in the intercept of the regression model. The choice of the undistracted driver as the reference level for distraction type was made consciously to aid in comparison between the undistracted and distracted driving conditions. Likewise the choice of the first queue position creates a more logical interpretation of the data than other choices of queue position. The reference levels chosen for state and lane position are completely arbitrary, but it was necessary to set a reference level for the model. Equation 4 shows the full model.

$$medain\big(Log(headway)\big) = \beta_0 + \beta_1 * Oregon\ + \beta_2 * Utah\ + \beta_3 * Pos2 + \beta_4 * Pos3\ +\ \beta_5 * Pos4\ + \beta_6\ * Pos5 + \beta_7 * Cell + \beta_8 * Eat + \beta_9 * Talk\ + \beta_{10} * Dash + \beta_{11} * Other + \beta_{12} *\ Unknown + \beta_{13} *\ Inside \tag{4}$$

Where Dummy Variables are define as:

Oregon - intersection approaches in the state of Oregon
Utah - intersection approaches in the state of Utah
Pos2 - vehicles in the second queue position
Pos3 - vehicles in the third queue position
Pos4 - vehicles in the fourth queue position
Pos5 - vehicles in the fifth queue position
Cell - drivers distracted by a cell phone
Eat - drivers distracted eating or smoking
Talk -drivers distracted by talking
Dash - drivers distracted manipulating the dash board
Other - drivers distracted any other distraction
Unknown - drivers who’s distraction could not be observed
Inside - position in the dual left-turn lane

4.5 Model Diagnostics

To examine the suitability of the full model (Equation 4) for further interpretation using multiple linear regression methods, several diagnostics tools were used. These included a Q-Q plot, residual plot, Cook’s distance, and the variance inflation factor (VIF).

4.5.1 Q-Q Plot

A normal Q-Q plot was created for the full model (Equation 4). The balanced S-shape of the plot, with the majority of the points directly on the Q-Q line, show that the log transformed data closely matches the normal distribution (Figure 17). The lift of the tails away from the line is a sign of heavy tails on both sides of the normal distribution, but should not pose a problem in the linear regression analysis.

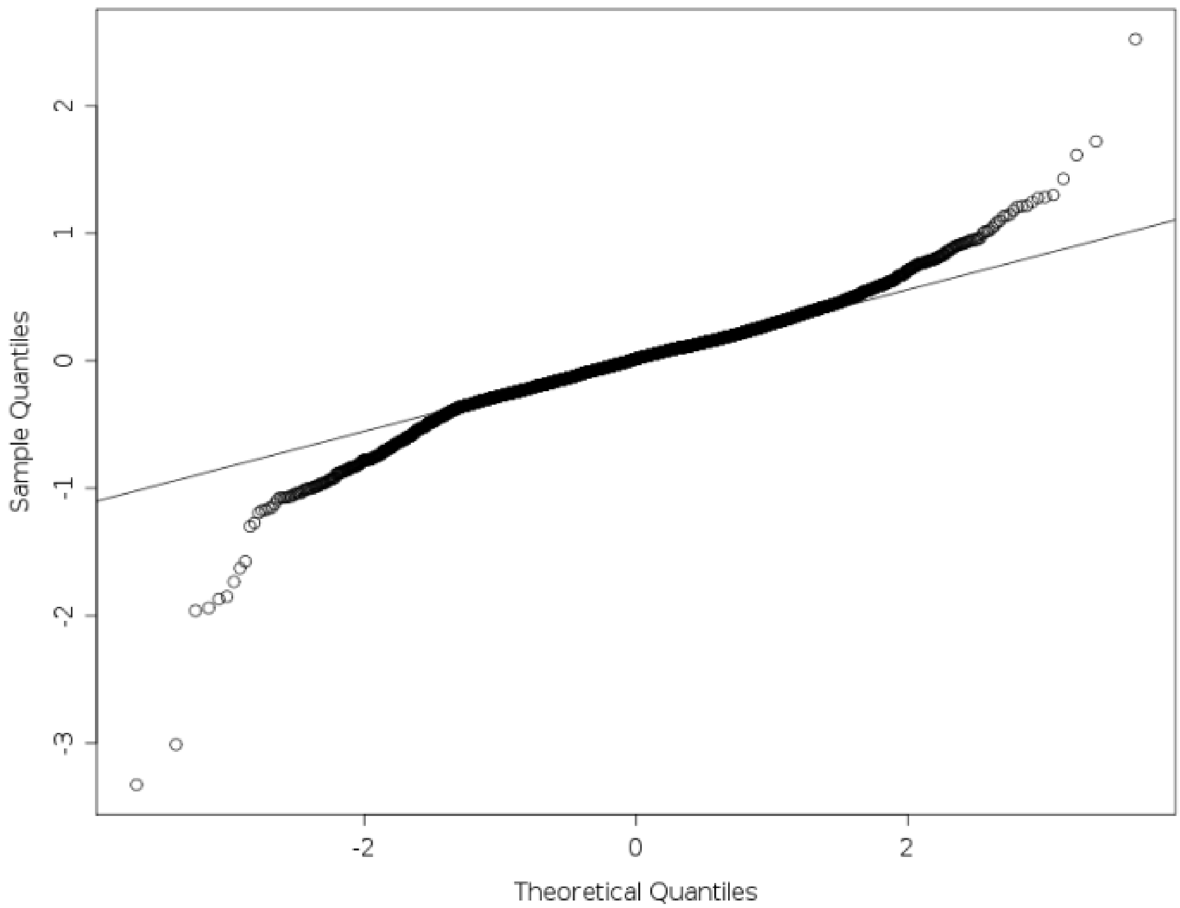


Figure 17: Normal Q-Q Plot for Raw Headway Data from Queue Position 1-5

4.5.2 Residual Plot

Second, a residual plot was created for the full model (Equation 4). The residual plot shows an equal distribution around the zero line indicating that the data set has relatively equal variance and is suitable for linear regression (Figure 18).

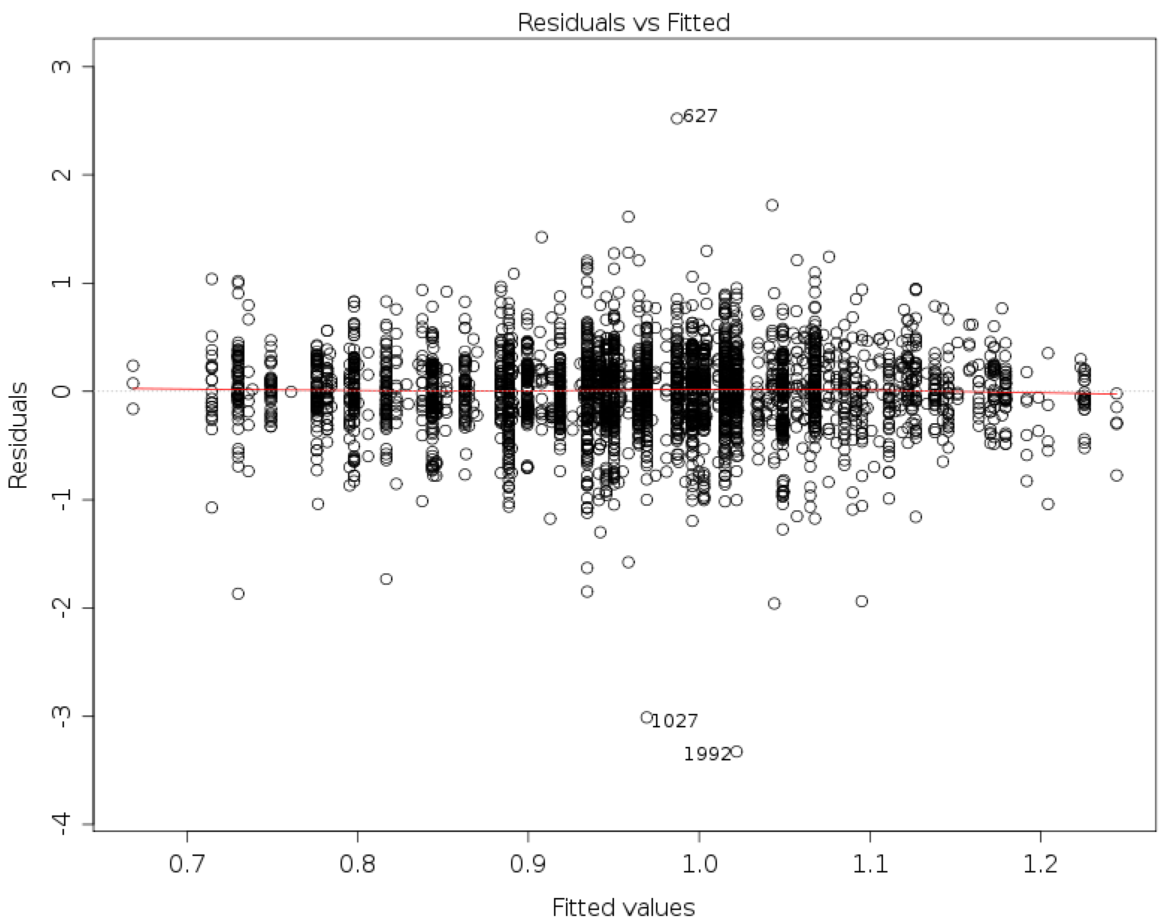


Figure 18: Residual Plot of Full Model

4.5.3 Cook's Distance

Next, a plot of the standardized residual vs. the leverage was created to examine if any points were highly influential on the model. Cook's distance was plotted on this graph at a value of 0.05. Generally, a value one is used as a rule of thumb for determining if a point is influential. The data set has no points that cross the 0.05 Cook's distance line verifying that no points have undue influence in the model (Figure 19).

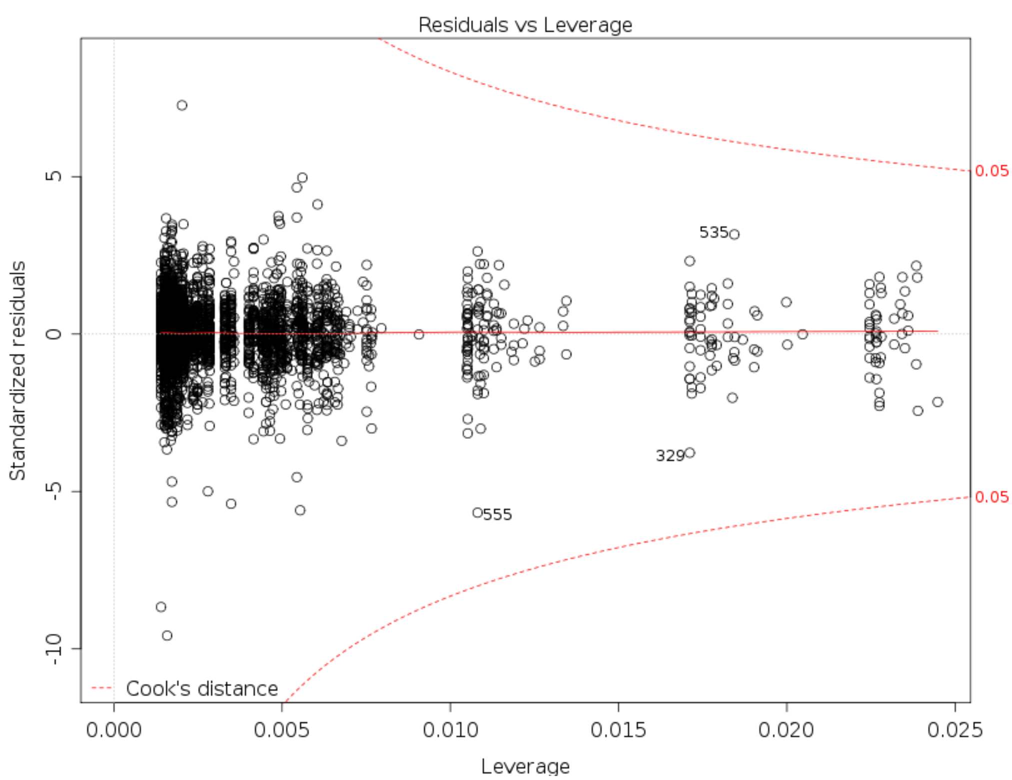


Figure 19: Standardized Residual vs. Leverage

4.5.4 Variance inflation factor

Finally, the model (Equation 4) was checked for multicollinearity using the variance inflation factor (VIF). Multicollinearity exists when multiple independent variables in a model are attempting to explain the same variability within that model. This can result in a situation where small changes in the data can produce drastic and erratic changes in the estimates associated each of the independent variables. As a rule of thumb, VIF values of greater than five are considered a sign of multicollinearity. None of the VIF values for the full model (equation 4) are above 1.85 (Table 6) indicating that multicollinearity is not an issue.

Table 6: VIF by Dummy Variable

Variable	VIF
Oregon	1.753
Utah	1.842
Pos 2	1.318
Pos 3	1.300
Pos 4	1.248
Pos 5	1.195
Cell	1.031
Eat	1.018
Talk	1.040
Dash	1.011
Other	1.013
Unknown	1.043
Inside	1.024

4.5.5 Diagnostic Summary

The diagnostic tests all show positive results regarding the use of linear regression on the log transformed data. The Q-Q plot has shown that the data fits the normal distribution reasonably well, and the residual plot shows there is roughly equal variance within the data. Further, the Cook's distance has shown that no points within the data set are exhibiting an undue influence on the model. Finally, the VIF has shown that the independent variables in the model are not trying to explain the same variability in the headway data. The four diagnostic tests, in aggregate, provide evidence that the full model (Equation 4) is suitable for further regression analysis.

4.6 Choosing the Best Model for Headway

Next, several reduced models were created to answer questions about which of the independent variables should be included in the best model of the headway data. These models are based on the full model (Equation 4) and remove one of the independent variables (distraction, state, left-turn lane position, and queue position) from the model at a time.

4.6.1 Does Distraction Affect Headway?

The first question that must be answered is, "should distraction be included in the model to explain headways in standing queues at dual left-turns?" To determine if distraction has an effect on headway a reduced model was created (Equation 5) that does not contain terms for the different distraction types (*Cell Phone, Eat, Talk, Dash, Other, Undistracted, and Unknown).*

$$medain\big(Log(headway)\big) = \beta_0 + \beta_1 * Oregon + \beta_2 * Utah + \beta_3 * Pos2 + \beta_4 * Pos3 + \beta_5 * Pos4 + \beta_6 * Pos5 + \beta_{13} * Outside \quad (5)$$

Where:

All variables are defined in Equation 4

An extra sum of squares F-test was used to compare the reduced model (Equation 5) to the full model (Equation 4) to determine which model better explains the variation in headways. The null hypothesis for this test is:

H_0: There is no effect on headway caused by driver distraction
(or H_0: $\beta_7 = \beta_8 = \beta_9 = \beta_{10} = \beta_{11} = \beta_{12} = 0$)

The result of the F-test showed strong evidence ($p\text{-value} < 0.001$) to reject the null hypothesis. Therefore one or more of the distraction types was a significant factor on the headway of drivers in standing queues at dual left-turn lanes. This showed that the full model (Equation 4) explains the headway data better than the reduced model (Equation 5). From this it was concluded that distraction does indeed affect headways in standing queues at dual left- turn lanes and should be included as an independent variable in the best model.

4.6.2 Does the State of the Driver Affect Headway?

Previously a proportion test was preformed (see section 4.2) that showed the proportions of distracted driving were different between the three states. This was used as evidence to justify the inclusion of state in the full model. An F-test was used to confirm this assumption and a reduced model (equation 6) was created without the terms associated with state (*Oregon, Utah, or Kansas)*.

$$\begin{aligned} medain\big(Log(headway)\big) = \beta_0 + \beta_3 * Pos2 + \beta_4 * Pos3 + \beta_5 * Pos4 \\ + \beta_6 * Pos5 + \beta_7 * Cell + \beta_8 * Eat + \beta_9 * Talk + \beta_{10} * Dash \\ + \beta_{11} * Other + \beta_{12} * Unknown + \beta_{13} * Outside \end{aligned} \quad (6)$$

Where:

All variables are defined in Equation 4

An extra sum of squares F-test was used to compare the full model (equation 4) to the reduced model (equation 6) with the null hypothesis:

H_0: The state that the driver is in has no effect on headway
(or H_0: $\beta_1 = \beta_2 = 0$)

The result of this F-test showed strong evidence (p-value<0.001) to reject the null hypothesis. Therefore one or more of the states was a significant factor on the headways of drivers in standing queues at dual left-turn lanes. This showed that the full model (Equation 4) explains more of the variance in the headway data then the reduced model

(Equation 6). From this it was concluded the state of the drives does affect the median headways in standing queues at dual left-turn lanes, and should be included as an independent variable in the best model.

4.6.3 Does Left-Turn Lane Position Affect Headway?

Next, an F-test was used to test if the left-turn lane position explained any additional variability in the headway data and should be included in the best model. It was expected from the work of Shao and Wang, and Stokes et al. that left-turn lane position could be important to the model (2011, 1986). However, it was necessary to test this for the data set under consideration. A reduced model (Equation 7) was created, this time without the term associated with left-turn lane position (*Outside or Inside)*.

$$\begin{aligned} medain\big(Log(headway)\big) = {} & \beta_0 + \beta_1 * Oregon + \beta_2 * Utah + \beta_3 * Pos2 \\ & + \beta_4 * Pos3 + \beta_5 * Pos4 + \beta_6 * Pos5 + \beta_7 * Cell + \beta_8 * Eat \\ & + \beta_9 * Talk + \beta_{10} * Dash + \beta_{11} * Other + \beta_{12} * Unknown \end{aligned} \tag{7}$$

Where:

All variables are defined in Equation 4

An extra sum of squares F-test was used to compare the full model (Equation 4) to the reduced model (Equation 7) with the null hypothesis:

H_0: The left-turn lane position has no effect on headway
(or H_0: β_{13}= 0)

The result of this F-test showed strong evidence (p-value<0.001) to reject the null hypothesis. This showed that the full model (Equation 4) explains more of the variance in the headway data then the reduced model (Equation 7). Therefore the left-turn lane position was a significant factor on the headways of drivers in standing queues at dual left- turn lanes, and should be included in the best model.

4.6.4 Does Queue Position Affect Headway?

Finally, whether or not to include queue position as an independent variable was examined. From an overwhelming consensus in the literature, it was expected that queue position would be important to the model (Koonce et al. 2008, Mannering 2009, Roess et al. 2011, HCM 2010). A reduced model (Equation 8) was created without the terms associated with queue position (*Pos1, Pos2, Pos3, Pos4, and Pos5).*

$$medain\big(Log(headway)\big) = \beta_0 + \beta_1 * Oregon + \beta_2 * Utah + \beta_8 * Eat + \beta_9 * Talk + \beta_{10} * Dash + \beta_{11} * Other + \beta_{12} * Unknown + \beta_{13} * Outside \tag{8}$$

Where:

All variables are defined in Equation 4

An extra sum of squares F-test was used to compare the full model (Equation 4) to the reduced model (Equation 8) with the null hypothesis:

H_0: queue position has no effect on headway
(or H_0: $\beta_3 = \beta_4 = \beta_5 = \beta_6 = \beta_7 = 0$)

The result of this F-test showed strong evidence (p-value<0.001) to reject the null hypothesis. This showed that the full model (Equation 4) explains more of the variance in the headway data then the reduced model (Equation 8). Therefore the queue position was a significant factor on the headways of drivers in standing queues at dual left- turn lanes, and should be included in the best model.

4.6.5 The Best Model

From the series of F-tests it was shown that the independent variables distraction, state, queue position, and left-turn lane position should be included in the best model for estimating median headway in standing queues at dual left-turn lanes. In essence it was shown that the full model (Equation 4) explains the more variability in the headway data better than any of the reduced models (Equation 5, Equation 6, Equation 7, and Equation 8). From this it was conclude that the best model to predict the headway of drivers in standing queues at dual left- turn lanes is the full model (Equation 4).

$$\begin{aligned} medain\big(Log(headway)\big) = {} & \beta_0 + \beta_1 * Oregon + \beta_2 * Utah + \beta_3 * Pos2 \\ & + \beta_4 * Pos3 + \beta_5 * Pos4 + \beta_6 * Pos5 + \beta_7 * Cell + \beta_8 * Eat \\ & + \beta_9 * Talk + \beta_{10} * Dash + \beta_{11} * Other + \beta_{12} * Unknown \\ & + \beta_{13} * Outside \end{aligned} \qquad (4)$$

Where:

All variables are defined in Equation 4

4.7 Interpreting the Best Model

Once the best model was determined, a series of potentially more interesting questions were examined. Estimates as to the effect of each level of the independent variables on the headway of drivers in standing queues at dual left-turn lanes were created. Table 7 shows estimates and 95% confidence intervals (CI) for the 14 regression coefficients (or betas) from full model (Equation 4).

Table 7: Regression Coefficients from Full Model (Equation 4)

Dummy Name	Beta Estimate	Lower CI	Upper CI
Intercept	0.888	0.859	0.918
Oregon	0.081	0.051	0.110
Utah	0.062	0.033	0.090
Cell	0.047	-0.002	0.095
Eat	0.054	-0.035	0.142
Talk	0.177	0.135	0.218
Dash	0.111	0.010	0.213
Other	0.155	0.088	0.223
Unknown	0.070	0.027	0.113
Pos2	0.053	0.025	0.080
Pos3	-0.051	-0.082	-0.020
Pos4	-0.152	-0.188	-0.117
Pos5	-0.220	-0.262	-0.178
Inside	0.046	0.025	0.067

Because a log transform was used on the dependent variable headway, the values of these coefficients must be exponentiated before they can be interpreted. Table 8 shows estimates and 95% confidence levels for the 14 regression coefficients from the full model (Equation 4).

Table 8: Interpretation of Regression Coefficients from Full Model (Equation 4)

Variable Dummy Name	Beta Interpretation	Lower CI Interpretation	Upper CI Interpretation
Intercept	2.431	2.360	2.504
Oregon	1.084	1.053	1.116
Utah	1.064	1.033	1.095
Cell	1.048	0.998	1.100
Eat	1.055	0.966	1.153
Talk	1.193	1.145	1.244
Dash	1.118	1.010	1.237
Other	1.168	1.092	1.250
Unknown	1.073	1.027	1.120
Pos2	1.054	1.026	1.083
Pos3	0.951	0.922	0.980
Pos4	0.859	0.829	0.890
Pos5	0.803	0.769	0.837
Inside	1.047	1.025	1.070

Recall that in the full model the reference level was an undistracted driver in the state of Kansas in the outside turn lane. The *intercept* estimate will account for the reference level variables. In other words, it is estimated that the median headway of undistracted drivers in the state of Kansas in the outside turn lane is 2.43 seconds (Table 8). It is from this reference level and this initial value that the effects of distraction, queue position, lane position and state can be estimated.

To estimate the median headway of any driver other than the reference level the transformed regression coefficients are interpreted as multiplicative factors. For example, it is estimated that the median headway of drivers in Oregon, in the inside turn lane, in the third queue position, adjusting the dashboard controls would have a median headway 1.21 (1.084 x 1.047 x 0.915 x 1.118 = 1.21) times greater than of the reference level, or 2.93 seconds. The same process could be used to estimate the median headway of drivers with any combination of the independent variables by multiplying the appropriate the regression coefficient estimates together.

5. Results and Discussion

Now that the best model has been determined and the regression coefficients have been interpreted in a meaningful way, a discussion about the significance of these results can commence. It will be useful to look at each of the independent variables in this discussion and examine what information they tell us about the median headway of drivers.

5.1 Discussion of the Variable State

It was shown that there are differences in the proportions of distraction type between the three states Utah, Kansas, and Oregon (see section 4.2). Also, it was proven that there is a statistically significant difference in the headways between the three states through the F-test comparing full model (Equation 4) and the reduced model described by Equation 6. However, it is important to carefully examine the data encompassed by the State variable.

As described in the methods section, the data for this experiment was collected from 11 intersection approaches with dual left-turn lanes in Corvallis, Oregon, Logan, Utah, and Lawrence, Kansans. These locations were not randomly chosen from within the three states. Rather, these sites were covenant locations for the researchers to access. The regression coefficients for the different variable state do not truly represent a difference in headway between these states, but rather a difference in headway between these three cities (or even more specifically, these intersection approaches). Although, these cities share many similarities, they are all relatively small cities with large state universities in the western United States; it would be disingenuous to attribute the difference described by the variable state solely to the effect of being in Kansas, Utah, or Oregon. There are simply too many uncontrolled variables that exist between these sites. The fact that a difference can be seen in the independent variable state should provide evidence to support the idea that a difference in headways may exist between different regions in the United States.

As far as the magnitude of the difference in headways that could be expected in different regions of the United States, limited conclusions can be made. Corvallis, Oregon was found to have headways greater than Lawrence, Kansas by a factor of 1.08 (95% CI from 1.05 to 1.12), and Logan, Utah was found to have headways greater than Lawrence, Kansas by a factor of 1.06 (95% CI from 1.03 to 1.10). Comparing Corvallis, Oregon to Logan, Utah (a process that requires setting either Oregon or Utah as the reference level in the model and recalculating the regression coefficients) shows that Logan is expected to have headways only 0.98 (95% CI from 0.96 to 1.01) that of Corvallis. It should be note that the 95% CI for the difference in headway between Corvallis and Logan contains the value 1.00, indicating that there may not be a difference between these two locations. If more locations were examined, it would be surprising to find differences in other cities that were vastly greater than the values reported; however without data this is only speculation.

5.2 Discussion of the Variable Left-Turn Lane Position

From the literature, the capacity of dual left-turn lanes has been shown be about 1.8 that of a single left-turn lane, rather than the theoretical maximum of 2.0 (Capelle and Pinnell 1961, Leisch 1967). This supports the idea that there may be a difference in the characteristics of the two turn lanes. Further, Stokes et al. and Shao and Wang report differences in the values for the saturation headway between the inside and outside turn lanes (1986, 2011). However, there is little consensus as to which lane, the inside or outside, has a higher or lower headways.

The result of the regression analysis shows the median headway of vehicles in the inside lane to be larger than that of vehicles in the outside lane by a factor of 1.05 (95% CI from 1.03 to 1.07). These larger headways would contribute to a lower capacity in the inside lane compared to the outside lane.

5.3 Discussion of the Variable Queue Position

The literature documents a clearly defined trend for the headways of the first five vehicles (Figure 2). However, if one were to plot the predicted headways from the best model (Equation 4) one would see a slightly different trend (Figure 20).

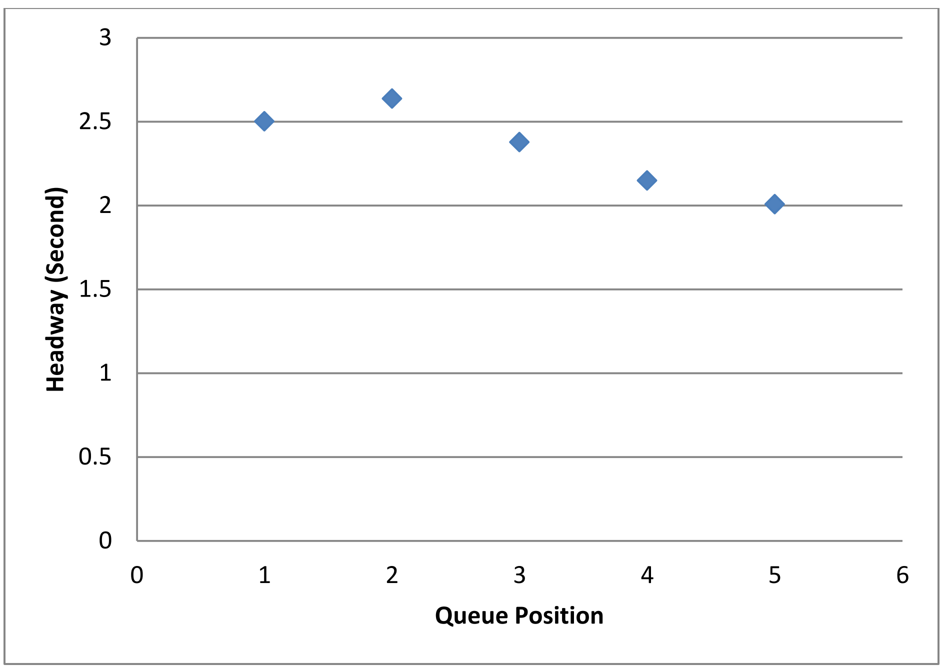


Figure 20: Expected Headways from the Full Model (Equation 4) Based on an Initial 2.5 Second Headway

Although Figure 20 shows a general agreement with Figure 2, the headway way of the first queue position is unexpectedly low. This discrepancy was initially concerning because the literature is unanimous that headways at signalized intersection show the trend described in Figure 2, but the discrepancy has a logical explanation. Referring back to the methods section, the camera was used to collect the data on the timing of the signals at the intersections. To create a record of the signal timing a researcher watched the signal and shouted “red light” or “green light” each time the signal changed. This process allowed the data to be collected with the limited resources available, but it introduced a PRT error into the first headway measurement. If an average PRT value, for example the 0.66 second that Johansson and Rumar report in 1971, were added to the expected values the result (Figure 21) would match the trend in Figure 2 as expected.

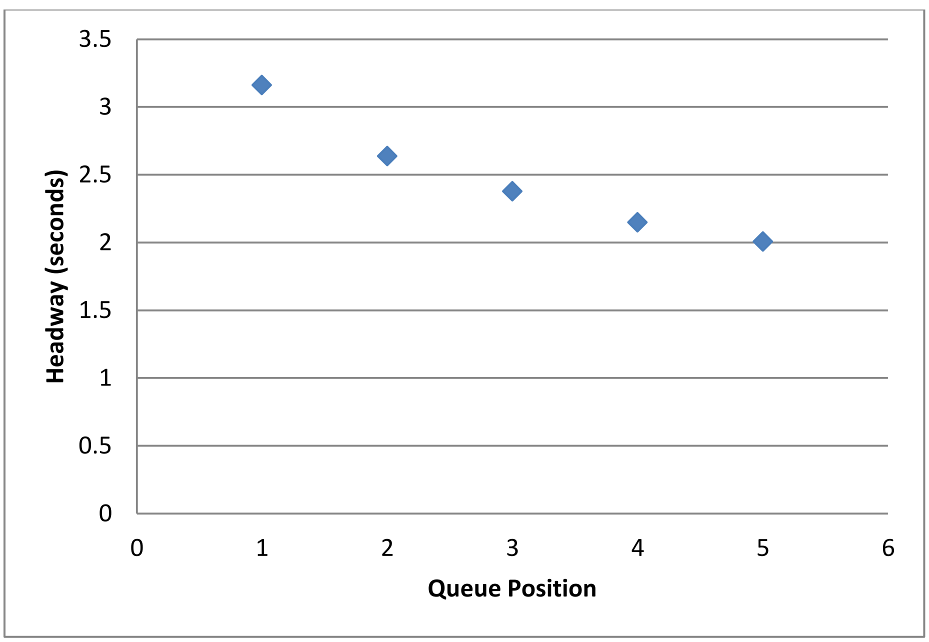


Figure 21: PRT Corrected Expected Headways from the Full Model (Equation 4) Based on an Initial 2.5 Second Headway

5.4 Discussion of the Variable Distraction

There is a variety of literature about different distractions and how they can affect drivers. Some such as Glaze & Ellis, McEvoy et al., or Regan et al. have related distraction to the likelihood of a crash (2003, 2005, 2008). Others such as Strayer et al. or Simons-Morton have related distractions to characteristics such as PRT or headway (2003, 2005). However, these studies have one thing in common; they view distraction as a negative due to its effect on safety. While this is undoubtedly true, there is little known about how distraction behavior affects the efficiency of the transportation system.

5.4.1 Interpretation of the Regression Estimates

The regression analysis performed allows the effect of the individual distraction types to be quantified as a comparison to an undistracted driver. From the F-test performed between full model (Equation 4) and the reduced model described by Equation 5 there is strong evidence that one or more of the distraction types are significant factors in explaining the headway of vehicles in standing queues at dual left-turns.

Table 9 shows the multiplicative factor by which the median headway of a driver is expected to change when the driver is experiencing each distraction type. It should be noted that data for drivers experiencing multiple distractions was not included in the analysis and it would not be appropriate to multiply these factors together to create an estimate of a driver experiencing two or more distractions.

Table 9: Estimated Effects of Distraction Types

Distraction	Estimated effect	Lower CI interpretation	Lower CI interpretation	p-Value
Cell phone Use	1.048	0.998	1.100	0.060
Eat or Smoking	1.055	0.966	1.153	0.235
Talking	1.193	1.145	1.244	<0.001
Manipulating Dashboard	1.118	1.010	1.237	0.032
Other Distraction	1.168	1.092	1.250	<0.001
Unknown Distraction	1.073	1.027	1.120	0.001

The estimated median headway of drivers with the different distractions range from 1.048 to 1.193 times greater than that of an undistracted driver. Imagining a relatively standard value for headway in a queue such as 2.5 seconds, these estimates translate into increased values of headway of a tenth of a second to nearly a half second.

Although an estimate can be made for any of the distraction types identified in the data set, some the differences are more significant than others. In fact some of the 95% CI contain the value of 1.000 indicating that there may not be a difference in median headway between some distracted drivers and undistracted drivers. For example the 95% CI for the effect of *eating or smoking* is from 0.966 to 1.153. Using this interval all that can truly be concluded is that the median headway of a driver *eating or smoking* is expected to be slightly smaller, or slightly greater, or exactly that of an undistracted driver. This lack of confidence in any effect of eating *or smoking* can also be seen in the high p-value associate with the estimated effect (p=0.235).

Likewise the 95% CI of *cell phone use* contains the value 1.000. However, here the interpretation is somewhat different. The p-value associated with *cell phone use* is 0.060. While this value is greater than the typical 0.05 cutoff for statistical significance, it is close enough to be suggestive of a true effect. With a larger data set this p-value would likely fall under the 0.05 p-value cut off and suggest a small increase in median headway of drivers distracted by *cell phone use.* All of the other estimates have p-values and CI that are clearly significant.

5.4.2 The Effect of *Cell phone Use* vs. *Talking* to a Passenger

There is a perception that use of a handheld cell phone has more negative impacts than other forms of conversation (National Safety Council 2010). Indeed, many states have introduced law mandating the use of hands free devices while driving despite the fact that multiple studies have shown that the conversation is the major distraction (Consiglio et al. 2003, Patten et al. 2004, Strayer 2007). The results of this analysis highlight an interesting situation where an in vehicle conversation may be more detrimental to driver performance than a cell phone conversation.

The estimated median headway for drivers talking with a passenger expected to increase by a factor of 1.193, but the estimated median headway for drivers using a cell phone is only expected to increase by a factor 1.048. This shows that in certain situations, such as while waiting at a red light, that a passenger conversation can have a greater effect on the performance of a driver than the oft vilified cell phone conversation. Although impossible to prove from the data, this effect could be caused by the additional visual distraction that a passenger presents.

As discussed before (see section 2.5), distractions are commonly described as some combination of physical, visual, or cognitive distraction. Both a conversation with a passenger and a cell phone clearly cause a cognitive distraction as the driver must process the information being heard and communicates information in response. The cell phone user has an additional manual distraction caused by the need to hold the phone, but is relatively free to devote their visual attention to the intersection and the traffic signal. The driver talking to a passenger in the vehicle does not have the manual distraction of holding the phone, but is presented with the visual distraction of looking at the passenger they are conversing with. The driver looking at a passenger may have a greater PRT as they split their visual attention between the passenger and the signalized intersection leading to greater headways.

5.4.3 Implications on Start-Up Lost Time

The start-up lost time was defined before as the sum of the incremental headways above the saturation headway (see section 2.1.3). Also, it is commonly accepted that vehicles will travel at the saturation headway after the fourth or fifth vehicle (Koonce et al. 2008, Mannering 2009, Roess et al. 2011, HCM 2010).

To estimate the saturation headway, the median headway of vehicles with queue position greater that five was taken. Since the saturation headway is not a single value that all drivers past queue position five will maintain, but rather a value that their headways will trend toward, the data set was reduced to those headways with in one standard deviation of the initial median value and then the median was recalculated. This refined value was used as an estimate for the saturation headway and was calculated for each state individually (Table 10).

Table 10: Saturation Headway Estimates by State

State	Saturation Headway (seconds)
Oregon	1.91
Utah	1.97
Kansas	1.93

Using these estimates of saturation headway the start-up lost time was calculated for a queue of undistracted drivers in each state by subtracting the estimated saturation headway from each of the expected headways of drivers in queue positions one through five, and summing the result. This process was then repeated using the expected headways of a queue consisting entirely of distracted drivers. Table 11 shows the expected start-up lost time for an undistracted queue of five drivers in each state, and the additional start-up lost time that would be expected from a queue where each driver is distracted by same distraction type.

Table 11: Start-up Lost Times

State	Start-up Lost Time (seconds)	Additional Start-Up Lost Time for Distracted Queue (seconds)					
		Cell	***Eat***	***Talk***	***Dash***	***Other***	***Unknown***
Oregon	2.75	0.59	0.68	2.38	1.45	2.07	0.89
Utah	2.22	0.58	0.66	2.33	1.42	2.03	0.87
Kansas	1.69	0.54	0.`63	2.19	1.34	1.91	0.82

Although a queue of drivers engaged in an identical distraction type is not the most likely occurrence, it is by no means an impossible one. However, it may be best to consider the additional start-up lost times from Table 11 as a range of additional lost times that could be expected in a distracted queue. As seen in Table 11 a distracted queue could have a start-up lost time from 0.54 seconds greater to 2.38 seconds greater than an undistracted queue.

5.4.4 Implications on Efficiency of Signalized Intersections

Finally, if one considers the timing of a standard four leg intersections, there being little guidance on the timing of intersection with dual left turn lanes, a discussion about efficacy can commence. It should be noted that because the data for this analysis come exclusively from dual left turn lanes, and not all of the movements present at a typical four leg intersection, this will require a small intuitive jump. However, in the absence of a more complete data set, the application of these finding can be justified for use in the following thought experiment.

Considering that a minimum cycle length of 60 seconds is suggested by the HCM 2010 for a four leg intersection, the increase of even the modest 0.54 seconds per leg would waste 3.6% of the available cycle length at the intersection. If the more alarmist value of 2.38 seconds were considered this percentage would jump to 15.9% of the cycle length being wasted by distracted drivers. This would represent a significant impact on the efficiency of the intersection.

6. Conclusion

Driver distraction is a prevalent condition among drivers, and the negative impacts of distraction are undeniable. Figures such as the 3,331 people killed, and 387,000 people injured in crashes involving distracted drivers in 2011 bring the negative safety aspects of driver distraction to the forefront of conversation, and rightfully so (NHTSA, 2013). Yet there is another negative impact of distraction that is commonly overlooked, the effect of driver distraction on efficiency.

This paper has examined the headways of vehicles in standing queues at signalized intersection with dual left-turn lanes, and the effect that distracted driver behavior is having on these headways. Using regression analysis four independent variables (queue position, state, left-turn lane, and distraction) were identified as significant predicators for the median headway of these vehicles.

6.1 Confirming for the Expected Effects

Before examining the effect of distraction it was first necessary to account for variables that are known to effect headway in standing queues. As expected from the previous work on driver behavior at signalized intersections the headways of driver in the data set under analysis was shown to follow the expected trend seen in Figure 2 (Koonce et al. 2008, Mannering 2009, Roess et al. 2011, HCM 2010). Additionally, significant regional variations in the proportions of distractions and headways observed were identified between intersection approaches observed in Kansas, Oregon, and Utah.

6.2 The Effect of Left-Turn Lane

Next because of the unique nature of dual left-turn lanes the effect of the inside or outside lane was considered. Shao and Wang, and Stokes et al. report headway data that suggested the inside and outside left-turn lane position may exhibit different headway patterns, but came to no consciences about which lane had larger headways (2011, 1986). The analysis in this study showed that vehicles in the inside lane of a dual left-turn lanes (Figure 4) have median headways that are 1.05 times greater than that of vehicles in the outside left-turn lane.

6.3 The Effect of Distraction on Headway

After accounting for the effects of queue position, regional differences between states, and the unique characteristics of dual left-turn lanes the effect of distraction was examined. Seven distraction types were identified in this study (*cell phone use, eating or smoking, talking to a passenger, manipulating the dashboard controls, other, undistracted, and unknown).* Of the six comparisons of a distracted driver to an undistracted driver the following four were found to have a significant effect ($p<0.05$):

- Drivers operating while *talking to passengers* had median headways 1.19 times greater than undistracted drivers.
- Drivers *manipulating the dashboard* controls had median headways 1.12 times greater than undistracted drivers.
- Drivers with *other* distraction had median headways 1.17 times greater than undistracted drivers.
- Drivers who were unable to be classified as distracted or undistracted (*unknown*) had median headways 1.07 times greater than undistracted drivers.

Additionally, suggestive evidence (p=0.06) was found that drives using a *cell phone* had median headways 1.05 times greater than undistracted drivers. No significant effect on median headway was found between drivers eating and smoking and undistracted drivers.

6.4 The Implications of Distraction on Start-Up Lost Time and Efficacy

The increase of headways of distracted drivers is by definition contributing to greater start-up lost times at intersections (see section 2.1.3). In the worst case scenario, a queue where all the drivers were conversing with passengers, the increase in lost time could be as high as 2.38 seconds for the dual left-turn movement.

6.5 The Interesting Difference between Conversation Types

This analysis showed strong evidence (p-value<0.001) of a 19% increase in headways of drivers talking to a passenger, and only suggestive evidence (p-value=0.06) of a 5% increase in headways of drivers talking on a cell phone. This shows in certain well defined situations the detrimental effect of a conversation with a passenger is greater than that of a conversation on a cell phone. While the exact cause of this phenomenon is not fully understood, it is hypothesized that while stopped at a signalized intersection a conversation with passenger creates a visual distraction that significantly increase PRT, and leads to greater headways and start-up lost times.

6.6 Potential Future Work

There is great potential for additional work on the topic of how distraction affects the efficiency of the transportation system. This study has only examined one very specific type of intersection lane configuration. Additional studies should be used to validate the effects of distraction on headway at intersection approaches with different lane configurations and allowed movements. Further this study has only examined the effects of distraction on efficiency at signalized intersections; the effects of distraction on efficiency in flowing traffic have not been addressed.

Additional, there is an unanswered question about why a passenger conversation has a greater effect on the headway of drivers than a cell phone conversation. Although it has been hypothesized that this is due to the visual distraction that the passenger creates, this hypothesis could be further investigated with eye tracking equipment.

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