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Using Hazard-Based Duration Models to investigate the Impacts of RUC on Libyan Drivers Travel Patterns

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ABSTRACT

This paper studies the perceived impacts of road user charging (RUC) on drivers daily activity travel patterns in urban areas by using one of the large Libyan cities (Benghazi) as the case study. The analysis uses full parametric hazard models and data from a field-based RUC experiment that was conducted in Benghazi. The database consists of activity-based travel durations. This paper focuses on the analysis of the durations of drivers travel-to-work trips and addresses the changes on the patterns of driver's trips over the study period to investigate the differences attributable to origin (home-based), time, gender and age as a result of the RUC impacts. The results indicate that RUC can have a positive impact in reducing traffic congestion with reduction of driver's trips crossing restricted areas during peak period by around 35.5%. The paper concludes that RUC could serve as a good instrument in reducing traffic congestion and in improving the environment in city centre of Benghazi. The results could be of benefit to transport policy makers.

Keywords: Activity-based travel patterns, Road user charging and hazard-based duration models.

1. Introduction

Road-user charging (RUC) can be defined as a method of collecting money from road users. Whittles, (2003) defined road pricing as an asset of ideas that can be applied in urban areas to charge road users particularly when they drive in urban areas. RUC is considered as a practical technique used to solve or reduce traffic congestion and transport problems.

To create charging policy that is effective against congestion, some trips would have to be cancelled, while others would have to adapt their mode of travel, destination, frequency or time of travel. This would mean a change both in the lifestyle and style of travelling of an individual or the whole household, and the change involves rescheduling activity patterns, in terms of where, when, how, and with whom these activities are scheduled during the day or week, in order to achieve their desired activity participation (Bowman and Ben-Akiva, 2001).

Many studies have used an activity-based approach to analyse the impact of road user charging on activity travel patterns using travel and activity data. Moreover, various field-based charging experimental studies have been done by investigating the user's behavioral response toward the hypothetical introducing of road user charging policy.

For instance, Hug et al.,(1997), Thorpe & Hill (2003), Francsics (1998), O'Mahony et al., (2000), Nielsen (2004) and Chow (2006) are the most studies that examined behavioral responses toward RUC and provided detailed information on how users could adopt their travel patterns over time in response to RUC. The common positive aspect of these field experimental studies is the use of real budget to achieve more realistic decision from the participants. This process of using real budget helps the researcher to enhance the validity of the experiment. Other worthy points are the use of peak period toll hours which are the effectiveness time that can be used for charging, point-based or cordon-based charging as the type of charging, multi-days data by recording activity travel data for two periods before and after introducing of road user charging.

In this study the approach pursues the examples that stated above by using a field-based RUC experiment, pre-paid experiment budget, cordon-based charging, morning peak period toll hours and multiple activity travel data (7days before and 7days after the introducing of RUC) to ascertain and document the perceived impacts of RUC on individuals activity travel patterns in Libya cities for a sample of 120 participants for the real experiment and 60 participants of another sample that uses as a control group.

2. Hazard-Based Duration Models

Hensher and Mannering (1994) were one of the early advocates of applying hazard models to travel demand and activity duration modelling. Bhat (1996) stated that hazard duration models are regarded as a useful tool that can be applied to activities and there is much evidence to suggest that the hazard theory is an appropriate tool for investigating parameters that influence changes in both activity type and the consequential demand for travel. Zhong and Hunt (2005) examined household weekend activity durations using hazard-based models. This work suggested that a fully parametric hazard model can be considered as a suitable model for activity and travel related modelling. Also, Zhong et al. (2005) showed that the four most widely used distributions of a fully parametric hazard are Weibull, Exponential, lognormal and log logistic.

Moreover, the hazard function can be used as a tool to compare different scenarios so that their differences can be highlighted. In this study, the analysis focuses on the comparison of the hazard function of travel-to-work trips collected as part of the field based RUC experiment. The analysis will seek to develop a deeper understanding of the changes that have taken place in the duration of the travel-to-work trips of the field-based experiment that conducted during two weeks in May, 2008 in Benghazi, Libya.

The next section of the paper provides a brief description of the data used in the analysis then explores which of 11 parametric models best fits the data used in this work and then presents the results. The analysis firstly looks at the entire data set collected over the study period to explore differences due to trip origin, gender and mode choice. Lastly conclusions are drawn.

3. Description of the Travel Data

Naturally, as stated above, the data used in this study were gathered by the researcher using field-based road user charging experiment in May, 2008 in Benghazi, Libya. In total, 81 driver's respondents completed the survey during the two weeks period; the sample size of the control group respondents was 36. The database consists of information regarding travel-related activities (activity travel diary) and individual and household information. The travel related activity data includes a range of trip information including origin, destination, mode of travel, journey purpose and start and end time for two weeks. Figure 1 explain the main features of RUC experiment that conducted in Benghazi, including the location of the

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cordon, type of charging scheme, restricted hours, enforcement system, toll level, type of data and type of sample.

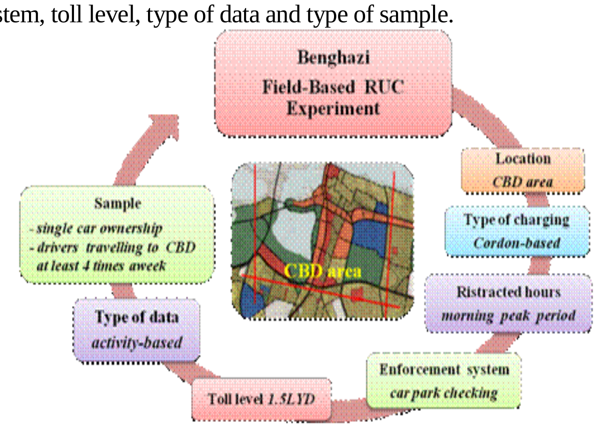

Fig. 1: The key features of road user charging experiment

4. Preliminary Findings of Road User Charging Impacts on Activity Travel Patterns

According to the field based RUC survey, the preliminary results show that;

- Around 68% (55 drivers) of the 81 drivers chose to pay the toll. A number of 46 drivers of the 81 (57%) chose to pay the charging toll on all the days of the experiment, however, 9 drivers of 81 (11%) chose to pay the toll for 3-4 days of the week. On the other hand, 26 drivers of 81 (32%) did not pay the toll at all and avoided the payment by choosing another alternative.
- During the first week of the study survey, drivers made a total of 2023 trips (or 25 trips per person per week, 3.5 per person daily, these results are mostly different with the previous results of Doxiadis (1989) that have been stated that it is about 1.8 trips per person daily.
- However, in the second week, the number of trips decreased by 3.3%. In the first week, the majority (97 %) of trips were by cars and only (3 %) of trips by other modes of travel. From these, one can see that the car was used as the main mode of travel for all the trips types.
- The daily travel patterns is classified into six trips types with respect to the "work" and "home" location namely; home-based, work-based, shopping- based, recreation-based, visiting-based and others-based that involve other different activities places. Based, recreation-based, visiting-based and others-based that involve other different activities places .
- Figure 2 shows that in the first week, the half (50%) of driver's trips were home-based trips, while nearly one-third (30%) were work-based trips, around 7% were shopping place-based trips, 5% visiting places-based trips and 3% recreation-based trips.

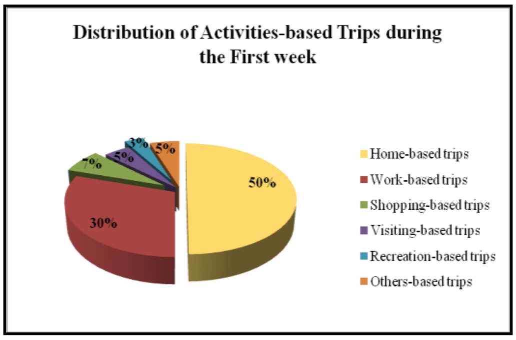

Fig. 2: Distribution of activity-based trips during the first week.

- In the first week the drivers made a total of 1006 home-based trips. Of these, 63% were home-based work trips while nearly one-third were home-based non-work trips such as home-based shopping trips 12%, home-based visiting trips 8%, home-based recreation trips 7% and home-based others trips 10%.
- Number of activity-based trips, and home-based work trips represent nearly two-third of all home-based trips. These results are generally different with the previous results of Libyan studies that have been stated that around 49% of trips are home-based travel to work trips (Doxiadis, 1989).
- Figure 3 illustrates the changes that have accrued on home-based activity travel trips during the second week. Furthermore, even though the percentage of home-based travel to work trips has slightly increased during the second week the number of travel to work trips has slightly decreased by 2.2%. Home-based shopping trips have decreased by 14.5 %, home-based recreation trips have decreased by 13%, and on the other hand, home-based visiting trips have increased by 13 %.

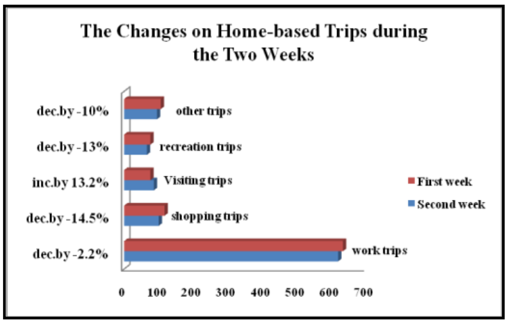

Fig.3: The changes on home-based trips during the two weeks

5. Using Hazard-Based Duration Models to Explain Changes in the Duration of Activity Travel during the Field Experiment

As mentioned previously, survival models or hazard-based duration models are common terms for the collection of models that characterise a probability distribution of the positive random variable T. A review of the literature indicates that while Hensher and Mannering (1994) started to present hazard-based duration models to travel demand modeling in a general way and gave an overview of the applications of these models to transport problems, a number of researchers tried to describe and analyse activity-based duration using hazard-based duration models. Safour (2012) explained the steps in the hazard model approach that applied in this section by clarifying the hazard theory and hazard functions also the steps in the application of the hazard theory.

5.1 Exploring the shape of the probability density function for durations of travel to work trips in the first week

According to Pas (1996), MOTOS Handbook (2008), and Statsoft (2008), there are three families of hazard duration model that can be applied to trip activity; fully parametric, semi-parametric and non-parametric. According to MOTOS Handbook (2008), and Statsoft (2008) the factor that determine the applicable method of hazard is the size of the sample of data, for instance, if the sample is large enough (e.i., 100 and more) the three families of hazard can be used. However, if the sample is small, then these three families can be applied if the data has normal distribution, otherwise, fully parametric hazard model is the suitable method to applied for a small number of

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observations.

In this study, full ranges of parametric functions were considered in the analysis of individuals daily travel durations in Benghazi during the first week of the field experiment. Examples of parametric models include Exponential, 2-parameter Exponential, Weibull, 3-parameter Weibull, Normal, Lognormal, 3-parameter Lognormal, Logistic, Loglogistic, 3-parameter Loglogistic and Smallest Extreme Value. According to Hensher and Button (2000) and Zhong et al.,(2005), the four largely used distributions in activity-based modelling are Weibull, Exponential, Lognormal and Loglogistic. Generally, the best fit model of these 11 models are identified based on various tests such as, the likelihood test, Anderson-Darling test and the Correlation Coefficients test (Hensher and Button, 2000). In this study, the Anderson-Darling (AD) test and the Correlation Coefficients (COR) test have chosen to evaluate the fit model. Zhong et al., (2005) mentioned a low value of the AD test and a COR value closest to 1 identify the best-fit model. As illustrated in Table 1, a 3-parameter lognormal distribution has the lowest value of the AD test and the highest value of the COR test for travel work trips, followed by the Lognormal distribution. However, the 3-parameter Lognormal has a negative threshold, which has no meaning in the context of duratin of travel. Therefore, the lognormal option is selected here as the best fit model.

Table 1: Goodness-of-fit tests for duration of travel to work for the first week

Distribution	Test Statistic	
	AD	COR
Weibull	56.877	0.897
3-parameter Weibull	24.868	0.914
Exponential	183.45	-
2-parameter Exponential	117.95	-
Normal	33.140	0.907
Lognormal	**24.001**	**0.949**
3-parameter lognormal*	23.775	0.949
Logistic	27.994	0.947
Loglogistic	83.873	0.811
3-parameter loglogistic *	26.58	0.947
Smallest extreme value	83.873	0.811
Best-fit model	**lognormal**	

* These distributions generate negative thresholds.

According to the above explanation, the next step was to check that the best fit model for the data for each week separately. The six most promising parametric distributions have been considered and the results presented in Table 2. All of these distributions have positive parameters with the threshold equal to zero. By comparing AD and COR values in Table 2, it is clear that the Lognormal distribution (statistically) is the best-suited distribution for the data, with the Loglogistic function having a similar performance. These two distributions were cited in the four (Weibull, Exponential, Lognormal and Log logistic) highlighted by Zhong (2005) and consistent with the Weibull distribution considered by Oh and Polak (2002). On the basis of this evidence the Lognormal distribution was adopted as the basis for this study.

Table 2: Goodness-of-fit tests for duration of travel to work for the data of two weeks

Distribution	Test Statistic Value			
	Week 1		Week 2	
	AD	COR	AD	COR
Weibull	56.877	0.897	19.637	0.934
Exponential	183.45	-	103.77	-
Normal	33.140	0.907	14.870	0.948
Lognormal	**24.001**	**0.949**	**12.006**	**0.954**
Logistic	27.994	0.947	18.317	0.939
Loglogistic	83.873	0.811	15.581	0.947
Best-fit model	**Lognormal**			

By normalizing the data it is possible to compare the disaggregated datasets and thus begin to understand the changes in travel work trip durations that have taken place over time and depending on other parameters such as time of travel, mode choice, and gender.

According to the Handbook (2008), and Statsoft (2008), the Lognormal probability density function f(t) is given by:

$$f(t) = \frac{1}{\sigma t\sqrt{2\pi}} exp\left[\frac{(\ln t - \mu)^2}{2\sigma^2}\right], t > 0 \qquad (1)$$

The cumulative distribution function $f(t)$:

$$f(t) = \int_{-\infty}^{t} \frac{1}{\sigma t\sqrt{2\pi}} exp\left[\frac{(\ln t - \mu)^2}{2\sigma^2}\right] dt \qquad (2)$$

The survival function is *S(t)*

$$S(t) = \int_{-\infty}^{t} \frac{1}{\sigma t\sqrt{2\pi}} exp\left[\frac{(\ln t - \mu)^2}{2\sigma^2}\right] dt \qquad (3)$$

Where: $\mu =$ the location parameter($\mu > 0$), and$\sigma =$ the scale parameter of the distribution ($\sigma > 0$).

Using the Lognormal density function the hazard theory is applied to total sample sets to develop the baseline results, which are presented in the next section.

6. Baseline Hazard for Travel to Work Trips Durations

As mentioned previously, hazard-based duration models will use to explain the changes on the travel patterns of commuter trips during the peak period of RUC experiment using a fully parametric method and Minitab software. To describe the hazard functions that used a number of Figures will illustrate the different situations of peak period travel using durations of travel to work trips.

6.1. Baseline hazard for travel to work trips durations in the first week

To explain the travel to work trips during the first week in the peak period a set of durations of trips of travel to work (commuter trips) has been applied using hazard based duration models. As mentioned above in table 2 the lognormal distribution is the best-fit distribution.

Firstly, as can be seen Figure 4 shows the probability density function (a), goodness of fit (b), survival function (c) and the hazard function (d) for travel or journey to work trip durations that conducted by the drivers participated in the first week of the study during peak period using the Lognormal distribution which is according to the AD and COR tests the best fitted model for the first week data. It also includes the parameter estimates and calculated statistics. Interpretation of these functions can be explained using the duration of 20 minutes of travel to work trips. It can be seen that the probability density function shows that 56% of travel to work trips have duration of 20 minutes. The goodness of fit plot (with correlation R = 0.94) indicates a very high degree of correlation between the lognormal distribution and the observed values. The largest deviation occurs for the shorter and longer journey times.

From the survival function (c) one can see that less than half of travel to work trips have a duration greater than 20 minutes and more than the half have durations less than or equal to 20 minutes. The hazard function presents the ratio of the probability of a given trip duration relative to the total number of trip durations greater than this particular duration (d). Longer and shorter duration trips than the duration at the maximum hazard value (here about 20 minutes) are more likely to remain because the hazard (the prevention or disincentive) is lower.

The discussion of each step of the hazard theory has been presented here for clarity and to ensure understanding of the basics.

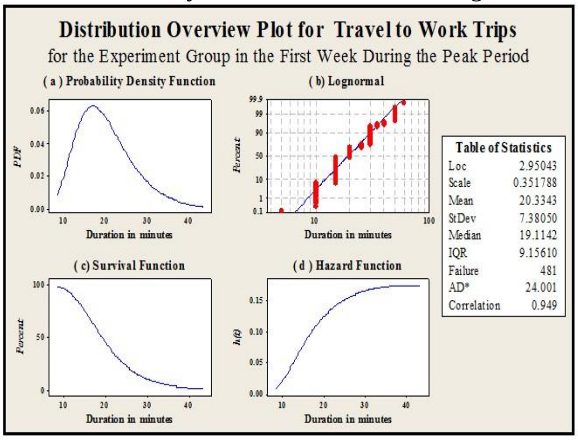

Fig.4: Distribution overview plot for duration of travel to work in the first week.

6.2. Baseline hazard for travel to work trips durations in the first week compared to the second week during the peak period

To investigate the changes that occurred on travel patterns during the second week of the field experiment of RUC, and according to the goodness of fit test the data of trips durations of travel to work during the peak period have applied using the baseline of hazard model and lognormal distribution which is the best fitted distribution for the field experiment data (Table 3).

Figure 5 shows the baseline hazard for durations of travel to work trips for the first week trips compared to second week trips during the peak period using two types of data (durations of trips by cars and durations of trips by other travel modes). The differences in the baseline hazard for travel to work trips in the second week during the peak period using cars and all other modes of travel and first week trips are evident from the Figure.

In general, for the first week, the hazard rate is higher for trips longer than about 12 minutes compared to second week trips durations for cars and other modes. The reverse is true for shorter than 10 minutes durations. This means that the disincentive to first week trips compared to the second week is respectively higher, and lower for shorter than 10 minute trip durations suggesting that the longer trips for the second week have more chance of surviving than for first week. This is counter intuitive result that indicates the most changes which have made during the second week were on the shorter trips more than longer trips.

Table 3: Goodness-of-fit tests for duration of travel to work for the second week trips using different modes

Distribution	Test Statistic Value			
	Week 2 (all mode trips)		Week 2 (car trips)	
	AD	COR	AD	COR
Weibull	19.64	0.934	30.32	0.907
Exponential	103.77	-	103.3	-
Normal	14.87	0.948	18.83	0.920
Lognormal	**12.01**	**0.954**	**14.63**	**0.951**
Logistic	18.32	0.939	21.58	0.914
Loglogistic	15.58	0.947	18.11	0.940
Best-fit model	**Lognormal**			

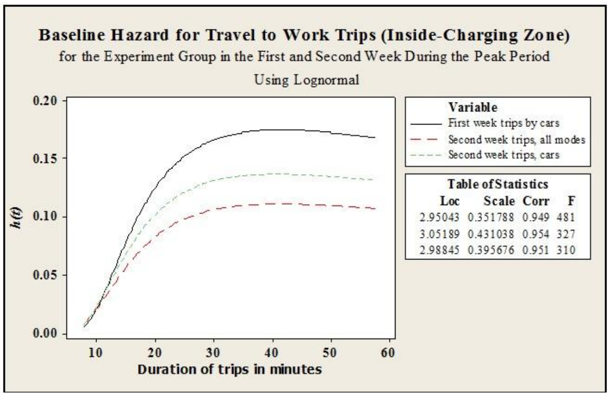

Fig. 5: Baseline hazard function for durations of travel to work trips in the first and second weeks using different modes of travel.

As stated above, the differences in the baseline hazard for durations of travel to work trips in the second week during the peak period using cars and other travel modes and first week trips is very clear. The Figure shows that the shape of the hazard function for car trips during the second week are (as expected)

different to the hazard shape for all modes trips; however, the difference is less than the difference to the first week cars trips. This is changes due to the fact that travel to work trips by car has shorter durations of travel than others modes trips such buses.

Moreover, in the second week car trips there was an increase in the hazard for shorter durations with change from all modes trips. In addition, it is clear that the maximum value of hazard rate has reduced for all modes trips during the second week suggesting shorter trips are surviving. The hazard curve again increases shifting slightly to higher deviations for cars than other modes.

6.3. Baseline hazard for travel to work trips durations for the control group

Another suggestion can be used to realise the changes that occurred during the second week after introducing the RUC scheme is the comparison study between the travel patterns of real experiment group (participated drivers of RUC experiment) and travel patterns of the control group (normal drivers).

Firstly, the study will use the control group data to recognise the main changes in the travel patterns during the two weeks of the study and Table 4 provides that the Lognormal distribution is the best suited distribution for durations of travel to work trips for the control group data during the peak period for the two weeks. From Figure 6, it can be seen that the shapes of the three functions; probability density function, survival function and hazard function are quite different for the first week trips of the control group and the second week. The control group trips trends are steady for the

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two weeks. This suggests that in general shorter and longer trips for the control group for the two weeks are remained without any changes compared to travel to work trips for the real experiment group which have significantly difference. This has been shown in Figure 5 for the real experiment group trips in second week, the longer trip durations have become longer and this due to the fact that a number of drivers who driving for short term have a chance to change their mode of travel from cars to other modes such as buses (which can be explain in more details by Figure 7 (a) and (b).

Table 4. Goodness-of-fit tests for durations of travel to work for the control group

Distribution	Test Statistic Value			
	Control group Week 1		Control group Week 2	
	AD	COR	AD	COR
Weibull	12.76	0.930	17.68	0.918
Exponential	75.15	-	76.6	-
Normal	8.62	0.951	11.24	0.940
Lognormal	**7.42**	**0.954**	**9.17**	**0.949**
Logistic	11.2	0.934	14.13	0.925
Loglogistic	9.49	0.938	11.62	0.935
Best-fit model	**Lognormal**			

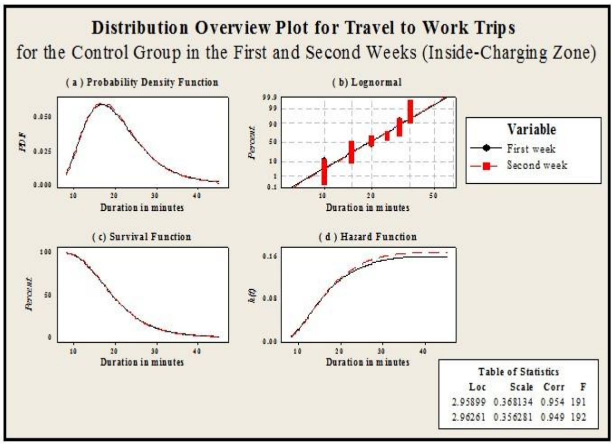

Fig. 6. Distribution overview plot for duration of control group travel to work trips

6.4. . Baseline hazard for travel to work trips durations for real experiment and control groups

In an attempt to gain further understanding of the changes of travel to work trips during the peak period of the field experiment of RUC using cars, control group trips were applied to compare with real experiment group trips. The results are presented in Figures 7(a) and (b). Figure 7(a) shows that the shapes of the hazard functions are quite similar for both experiment group and control group durations trips during the first week. A very little difference in the hazard rate of long durations for the experiment group durations trips where the hazard was higher.

It can be seen that the hazard rate dramatically increases with increasing trip duration until the trip duration reaches approximately 30 minutes. After that the hazard rate gradually steady with increasing durations of trip. However, the hazard values for the experiment trips a little bit higher than the control group trips for trips with 20 minutes durations and more. This suggests that in general longer trips for control group were much than longer for real experiment group trips comparing to the shorter trips for both groups. This suggested that the long durations trips for the control group more than durations trips of the experiment group comparing with the shorter trips. However, it is clear that the second week changes are quite different. The hazard values for the control group trips are higher than the experiment group trips.

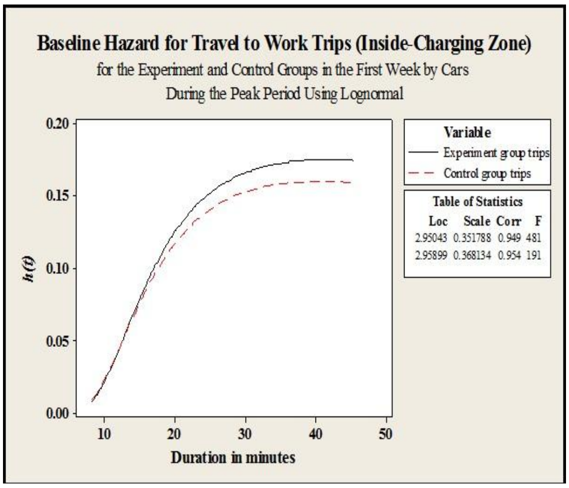

Fig. 7(a). Baseline hazard for peakperiod trips in the first week forreal experiment and control group

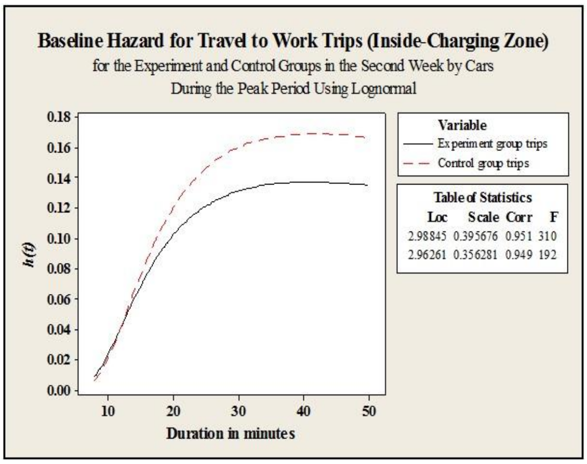

Fig. 7(b). Baseline hazard for peakperiod tripsin the second week for real experiment and control group

As has been seen from Figure 7(a) and (b) the shapes of hazard rates for the two weeks trips for the control group are similar. This suggests that the changes that occurred only with the real experiment group trips as has been shown in Figure 7(b). The decrease of hazard values for the real group trips in the second week means the decrease was in the trips of shorter durations. Also, it is clear in Figure 7(b) that the changes of hazard values starts from 15 minutes durations where the hazard curve increases slightly to higher deviation. This effect evident over such a short term is surprising because charging scheme effects are more likely to take place over shorter trips more than longer trips.

7. Conclusion

RUC is considered as a practical technique used to solve or reduce traffic congestion and transport problems. In Benghazi field-based RUC experiment the results stated that during the

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restricted hours, RUC policy can have a positive impact in reducing traffic congestion with reduction of car trips crossing restricted areas during peak period by around 35.5%. The results proved that the lognormal distribution presents the best fit for the journey-to-work trips data. The hazard function was used to gain a fundamental understanding of the characteristics of the changes in the patterns of travel during the study period have been presented. The research has indeed shown that the hazard theory does highlight interesting features that prove the positive impacts of road charging policy.

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