An Investigation to Uncertainty Dictating Queuing Behaviour with the Presence of a Time Constraint.

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Abstract

An investigation into consumer behaviour when presented with a queue, with and without the expected duration of the queue, for a typical lunch in town i.e. if you knew how fast your fast food would be would you be more likely to line up for it? [1] An initial observation of the natural queue every working day for two weeks, following which a non-intrusive nudge is introduced where by the members of the queue will be made aware of their expected waiting times in the form of a paper display in the window of the restaurant alongside which the queue forms. Data was collected by a GoPro camera outside the restaurant taking time-lapsed photos every half-second for two hours a day around lunchtime. The processed data was then analysed to fit a continuous time Poisson Process. concluding that the after recommencing the observations in the same manor with the addition of the nudge there existed an increase in both the average queue length and arrival rate implying that it perhaps increased the consumers willingness to queue.

[1] Your estimated reading time of this paper is 25 minutes

Contents

1 Introduction

The quantifiable cost of time is universally understood to be the concept underpinning opportunity cost, recent societal shifts have, furthermore, unearthed such discussions about time from academia to the forefront of popular consciousness. As markets continue to tap into the strong positive response to immediate gratification consumers display, time emerges as a crucial variable to which consumers attach significant weight.

It is apparent that consumers stand to gain utility if they are able to accurately gauge the amount of time inherently spent in any transaction. To do so would be to engage in more efficient, utility-gaining (or rather, saving) behaviour. Such information is, however, often unavailable and forces the consumer to make an estimate. If such information is subsequently provided and trusted, we might expect to observe a change in consumer behaviour towards a more efficient outcome for the market.

Its found that the time-related components of such a consumers choice architecture are preparation time and queue time. While the former is largely constant, queuing time is an uncertain and highly variable factor, and thus more susceptible to being incorrectly estimated. Therefore this experiment set to observe and record typical queue lengths and arrival parameters, so as to demonstrate a trend in either the under or over-estimation of utility the consumer believes he foregoes as a direct result of queue length.

This report hypothesises that frequent faulty approximation of time on the consumers' part leads them to forego transactions leading for them to be worse off. The choice architecture of a consumer's decision to join the queue for a burrito was thus examined.

1.1 The Roles of Expectations

When a consumer considers to consume a particular good, there is a number of *prior* expectations they have derived from their own assumptions. When a consumer analyses the choice architecture of a particular good, they derive *post* expectations of the good. Now the consumer possesses a post expectation and a realised expectation. The consumer can now make an informed decision based on the knowledge gained from the choice architecture. The difference in prior and post expectations will determine the consumer's final decision on whether or not to consume the good.

There is a plethora of variables within a choice architecture which can alter a consumers final decision. When presented with a decision, a consumer will consciously analyse the price, wait time and quality. These variables have a large effect on a consumers final utility received for a small deviation from the prior expectations of the consumer. Where as variables such as proximity, brand loyalty, taste and preferences are unlikely to change as they are part of the consumers everyday habit. The former variables can unexpectedly change and have a large effect on the final choice of the consumer, which in turn must have had an effect on the consumers post expectations.

There are varying degrees of uncertainty with in an expectation. A consumer will make a rational decision on their expectations but cannot be certain. This paper intends to investigate consumer behaviour when we remove or attempt to increase the certainty behind a consumers expectations.

1.2 The Total Cost of a Good

In this section we introduce how a consumer interprets a queue in their decision of whether or not to consume a good, and what aspects of this interpretation are relevant to our study.

When a consumer considers the cost of a good, they take into account the sale price of the good, $C_{saleprice}$, the cost of waiting in line, C_{wt} and the cost of travel C_{travel}. Where C_{wt} and C_{travel} are functions;

$$C_{wt} = \beta t \tag{1}$$

$$C_{travel} = \alpha t = \theta \tag{2}$$

Where the $t = waitingtime$. C_{travel} is constant as this would be included in a consumers everyday habits. β , represents the cost per unit time. This will vary amongst consumers. Total cost of the good to an individual, C_{total}, is therefore expressed as;

$$C_{total} = C_{saleprice} + \beta t + \theta \tag{3}$$

1.3 Expectations of Waiting Times

Consider the interpretation of parameter t by the consumer. This can either be known or unknown. If it is known, the consumer can then make an informed decision on whether or not to consume the good. For instance, when buying a car you are are told the expected delivery time. But what if this parameter is unknown to the consumer? This is often the case in many retail environments. A consumer sees a line of people all waiting to be served. Each member of the queue has made a conscious decision on whether or not to wait in line with their own expectations. All the customer may have to decide on is the appearance of the queue and their own estimation of the number of members occupying the queue. Based on these observations and basic assumptions, a consumer can derive an expected wait time. If the consumer's post expectations are more favoured than their prior, he may join the queue. If the customer's post expectation is less favoured than their prior, he may decide not to join the queue.

Suppose a consumer is presented with $X_1, X_2, \ldots, X_n$ options all with equal price, quality and equally satisfying the consumer's individual preferences. Assuming that this customer has at most βL_t to spend waiting in line. The potential customer considers the length of each queue and has different assumptions on each option affecting the wait time for each customer. Therefore each option has corresponding waiting times $E[wt_1], E[wt_2], \ldots, E[wt_n]$. The consumer will choose the option with the lowest corresponding waiting time $min_{i=1}^{i=n}[E[wt_i]]$. A consumer will only choose to purchase an option if; $E[wt_i] < L_t$. However this expectation was derived from imperfect knowledge so is random and subject to variation. The customers are therefore assumed to be;

subject to a time constraint; $L_t = L_0, L_1, \ldots, L_t$ and has a a maximum of L_0 to spend on decide upon their consumption and faces a monotonically decreasing constraint function L_t . This implies that the consumer is subject to an increasing cost function and $t = 1 - L_t$

loss averse; and not willing to wait in line if there is large variation in expectations. Hence, if there is large uncertainty, then a consumer will choose not to join the queue and may not consume at all.

subject to imperfect knowledge; and therefore will choose a restaurant randomly, with all restaurants being independently and identically distributed, i, i, d.

1.4 Arriving at a Distribution

With these assumptions in mind suppose $X = 1$ when a customer joins the queue and $X = 0$ signifies not joining the queue, with the following probability density function;

$$P(X = x) = \begin{cases} p \text{ when } x = 1, \\ 1 - p \text{ when } x = 0. \end{cases} \tag{4}$$

Examining this distribution with n customers in order to find the probability of having r arrivals for a given L_t. This will be given by the binomial distribution; $P(r) = \binom{n}{r} p^r (1-p)^{n-r}$.

let $p = \lambda/n$ and by taking the limit as $n \to \infty$, it can be shown that;

$$lim_{n\to\infty} P(r) = \frac{\exp(-\lambda)\lambda^r}{r!} \tag{5}$$

Where λ represents the parameter of a Poisson distribution and is the average number of people in the queue during a given interval corresponding to a *specific* L_t.

1.5 Removing Uncertainty

With these aspects in mind, the objective is to examine the behaviour of customers when the degree of uncertainty is minimised. In order to investigate this, we will observe a queue where there is no information conveyed to the customer and knowledge is imperfect. Through continual analysis of data collected from the queue, accurate estimated wait times were determined at specified points. These waiting times will be communicated to the customers corresponding with different points in the queue. The observations will then be recommenced in the same manor. It is expected that when a consumer is certain of their expected waiting time and their uncertainty minimised it will increase their willingngess to queue.

This report will explore the effect L_t has on the distribution parameter in a time series, with and without the nudge. A distribution was proposed in Section 1.4 with a poisson process parameter λ for a given time L_t and how the parameter λ changes as $L_t \to 0$.

2 Methodology

This section outlines the criteria to be met for this experiment, as well as the data collection and analysis practices.

2.1 Sampling of a Population

In order to investigate the human behaviour behind queuing, a large sample size was needed to compensate for the large variation amongst human decision making. The assumption has been made that each restaurant is equally likely to be selected and the distribution of arrivals of different restaurants was assumed to be *i.i.d.* Therefore it was needed only to analyse one restaurant's queue in order to investigate the behaviour of queuing.

It is necessary for the queue to be both predictable and have similar distributions throughout different days of the week. It needed to have a queue that was visible to customers from the street and thus it must extend out the door. Therefore a popular lunch time fast food restaurant was chosen. Here, there is a clear factor of L_t where by the later a person decides to eat lunch, the less time they have to spend on lunch.

$$\forall i > t, C_{T_i} < C_{T_t}, since, 1 - t = L_t \tag{6}$$

Mama's Revenge, located on Nassau St. is a popular Burrito Bar amongst workers and Trinity College Dublin students. It has a large amount of footfall passing at the same time every day. The service consists of hand made food to order.

The premises for the restaurant cannot contain the queue so the queue extends out onto the footpath and down past the front window of the shop. This made Mama's Revenge suitable for this experiment as the queue is clearly visible from the street. In addition service time is the same for all consumers and is part of a large sample of the population being studied.

2.2 Metrics of Interest

The queue will be measured in two different ways;

1. *Total Length of queue at a given time.*

   A record was taken of the number of participants in the queue at 90s intervals. This was chosen as the average time for a reduction of one in the queue was 90s. This meant the queue visually shifted every 90s approximately. This metric is a function of the amount of time a customer is in service for with arrivals being unchanged.

2. *Number of people joining the queue at any given time.*

   This is a function of human behaviour and humans interpretation of the queue. This can be see to be a Poisson distribution outlined in Section 1.4. Each arrival was treated as a separate event. Each observation consisted of a time stamp and the corresponding number of arrivals.

The first metric gives us an understanding of the size of the queue. This is important to investigate peoples willingness to join the queue at large queue lengths. This will hopefully reveal a relationship between the number of people joining a queue and the length of that queue, as the length of the queue is interpreted by consumers to derive their own $E[wt_i]$.

2.3 Time Frame of Observations

It was necessary to maximise the length of time to run the study, in order to minimise error in our observations and to extend the statistical significance of this report. The queue was therefore observed over four weeks, two weeks without the nudge and two weeks with the nudge in place, back to back. This resulted in two sets of *ten observations of a time series*. The timelapse was carried out each Monday to Friday from 14/11/2016 until 9/12/2016 during the lunchtime hours of 12:30 to 14:30. These times were the busiest for queue activity which were known observationally and confirmed by the restaurant. Such times allowed for collecting data on the queue from its minimum to its maximum for each day.

2.4 Method of Observation

A total of 40 hours of observations were required to meet the criteria of the study, thus it was called for to devise a way to condense observations into a shorter time frame to make it feasible to analyse. A discrete GoPro camera was used to record a time lapse for the two hours of lunch each day. The camera was put up every day at 12:30 and removed at 15:00. Data was then removed from camera memory, and charged every night before the next day of observations for 20 consecutive weekdays. The record criteria insisted that we only include participants of the the queue who are standing out of the door, as these customers chose to join under the choice architecture of a queue extending out the door.

2.5 Adding the Nudge

The nudge consisted of informing members and potential members of the queue with accurate waiting time estimations. These had to be clearly visible to consumers who are not a part of the queue as this would be used in their decision on whether or not they could wait in line for their food. Whatever was used also had to be able to last unobstructed for the length of the observations.

The nudge was decided as a series of clear posters featuring an arrow pointing to the consumer's current position in the queue, and their expected waiting time at that point. For instance "You are less than 4 minutes away from your burrito!". Four posters were introduced corresponding to times for twelve minutes, eight minutes, four minutes and less than four minutes. This nudge was in place for a total of 10 days during the last two weeks of observations.

2.6 Data Collection/Analysis

In order to statistically investigate the causality of uncertainty upon queue behaviour it was needed to convert the time lapse footage to a time series for each metric that was required to record. This involved collecting objective data from the time lapse with a time record of each event observed.

2.6.1 Collection

The queue was observed with a Go Pro capturing the entire length of the queue from a discrete location. The parameters for our observations are outlined in table 1.

Table 1: Time Lapse video Parameters

Parameter	Value
Capture rate	2/sec
Video Frame Rate	45 FPS
Real Time	2 hrs
Video Time	00:01:20
Daily memory	8 Gb

The first metric in Section 2.1 was recorded by counting every person in the queue manually at 90 second intervals. This was chosen as the customer moved along one step in the service process approximately every 90 seconds. This warranted 80 intervals with 10 observations for each set of data.

The second metric described in Section 2.1 was recorded by watching a slowed down version of the timelapses to 1/4 speed and recording arrivals to the queue. This allowed the use of a VBA program in Excel recording the time each data point was entered. This collection of 10 observations was then converted into a continuous time series using the 'zoo' package in R. This consisted of adding in observations as zero where there were no arrivals to the queue.

2.6.2 Analysis

The poisson distribution was computed for every 22.5s time interval using `rowMeans()` function in R to find the average number of people joining the queue for each 22.5 second interval. This resulted in two sets of 320 parameters. An ANOVA test was run in order to determine the statistical significance of the difference in groups.

Average length of queue is then plotted as a function of time. This provided a graphical representation of the appearance of the queue throughout the day. This yields another level of interpretation to the change in arrival parameters.

3 Summary of Data

This section outlines the main statistics used in the results and conclusions of this study.

3.1 Queue length

The first metric of interest; the total length of a queue at a given time is expressed in Figure 2 as the natural queue behaviour before the introduction of the nudge over a duration of two weeks, in Figure 3 as the nudged queue behaviour over the following two weeks, and a direct comparison of the two in Figure 1 with an average behaviour over the four weeks.

The minimum queue length of zero customers was naturally unchanged throughout the experiment, however a new maximum was achieved. As can be seen from Figure 1 & 2 the original maximum queue length observed was 16 customers during weeks 1 & 2, following which, the nudge was introduced and a new maximum of 18 customers was observed in both weeks 3 & 4. This results in an overall increase in the queue structure by two customers when given the expected waiting time.

The total length of a queue at a given time, compared by average number of customers presently in the queue, between weeks reveals that the nudge has led to an increase. The length for weeks 1 & 2 respectively was 3.82 and 4.20 (average of 4.01), which had a significant jump in weeks 3 & 4 to 5.42 and 6.39 (average of 5.91).

A notable trend that emerges across the four weeks in that the queue behaviour can be divided in to three distinct time frames of behaviour, namely between time intervals; $T1[12:30, 13:15], T2[13:15, 14:00]$, & $T3[14:00, 14:30]$. These time frames have distinct means as can be seen in Table 5 which tell us the relationship between the weeks before and after the nudge during these intervals. In the first time frame during the peak times for the restaurant we see a definite increase in average value after the nudge was introduced from 5.92 to 8.84. On the other hand, the second time frame $T2$ showed a trivial difference in contrast rising from 2.87 to 3.37. The nudge had a particular effect on the third time frame wherein a sharp increase was observed, and average values increased from 2.69 to 5.53.

An Anova Single Factor analysis at significance level of $\alpha = 1\%$ was run on the average queue lengths for the datasets before and after the nudge was introduced. The calculated p-value=0.000107 is lower than the chosen significance level suggesting statistical significance that our two datasets represent two distinct populations.

3.2 Queue Arrivals

The second metric of interest; the number of people joining the queue at any given time was averaged over each observation (days). The time series of average arrival parameters is plotted in Figures 4 & 5. This resulted in the decreasing regression line in scatter plot Figure 4 and the decreasing regression line in Figure 5. This shows that arrivals to the queue were decreasing over time. The highest number of arrivals at any given time is highest when the queue was busiest in $T1$, (Figure 1), as to be expected. When comparing the scatter plots in Figures 4 & 5, it is clear that arrivals were higher overall when the nudge was in place. The R^2 value increased significantly after the nudge. (See Table 6). Previously, time accounted for 8% of variance where as after the nudge, time accounted for 28.8% of the variance in arrivals, Figures **??** & **??** respectively.

Average arrivals in a day increased after the nudge (Table 6). The majority of these extra arrivals were in the interval $T1$. This is where the queue had the greatest average length. This can be seen in Figure 6 for $T1$. The 5 minute cumulated parameter is greater for all values in $T1$. When we examine the intercept of the regression line in the scatterplots previously mentioned, we see a higher intercept for after the nudge.

The two sets of parameters proved to be statistically significant at a 99 percent confidence interval. (Refer to the P-Value in Table 3) This shows that the nudge altered the arrival distribution of customers, from the visual representation of arrivals in Figures 4 and 5 it is clear this effect was predominantly seen in $T1$. There is large error with in groups, this is due to the time frame in which the observations were. (sSe 3).

The sample size of 20 days resulted in a high SSE value of 43.49 as is justified by the Within Group value of the One-way ANOVA table 3. This implies that 90% $(1 - R^2)$ of the model is explained by the existence of errors and is because of the high correlation between the average queue lengths of the 20 days. These high residual values are also explained by the presence of many outliers in the trend lines extracted before and after the nudge was introduced (Plots 4 & 5). This correlation stems from the fact that the market behaviour of the same restaurant was monitored over working days only. This Burrito Bar was popular among a similar crowd of people, usually students and office-goers, on these working days, even before the nudge was introduced.

3.3 Data Appendix

Table 2: ANOVA - Queue Length - 2 Groups of 10 days

			Summary			
Groups	Count	Sum	Average	Variance		
After	80	320.8	4.01	5.718		
Before	80	427.6	5.9075	12.523		
			ANOVA			
Source of Variation	SS	df	MS	F	P-Value	F-Crit
Between Groups	144.0202	1	144.0202	15.7901	0.0000107	3.901
Within Groups	1441.108	158	9.1209			
Total	1585.13	159				

Table 3: ANOVA - Arrivals - 2 Groups of 10 Days

			Summary			
Groups	Count	Sum	Average	Variance		
After	319	147.668	0.4629	0.1447		
Before	319	110.7813	0.3472	0.0706		
			ANOVA			
Source of Variation	SS	df	MS	F	P-value	F crit
Between Groups	6.334	1	6.334	758.8435	6.432E-14	3.856
Within Groups	68.458	636	0.108			
Total	74.791	637				

Table 4: Min/Max Summary

	Min Length	Max Length	σ	Average Customers
Week 1	0	16	3.53	3.82
Week 2	0	16	4.09	4.20
Natural (1&2)	0	16	3.53	4.01
Week 3	0	18	5.05	5.43
Week 4	0	18	4.26	6.39
Nudged (3&4)	0	18	4.69	5.91
Total Queue Behaviour	0	18	4.31	4.91

Table 5: Average Before/After Summary

	μ_{Before}	μ_{After}	σ_{Before}	σ_{After}
$T1[12:30, 13:15]$	5.92	8.84	2.76	2.83
$T2[13:15, 14:00]$	2.87	3.37	1.20	0.71
$T3[14:00, 14:30]$	2.69	5.53	1.706	6.36

Table 6: Arrival Statistic Summary

	After		Before	
	Max	Min	Max	Min
λ	1.601	1.396	1.505	0
λ_5	12.1926	3.4689	7.299	1.444
λ_{10}	22.9286	3.4689	13.0759	4.365
λ_{15}	32.954	6.0444	18.3177	7.126
$P(x = N\|\lambda_5)$	Max	Min	Max	Min
0	0.29	1.90E-05	0.2468	2.21E-06
1	0.36	1.76E-06	0.256	1.50E-06
2	0.21	9.90E-06	0.253	5.10E-08
3	0.245	2.46E-06	0.24858	3.42E-06
4	0.4	1.05E-06	0.259	5.10E-09
Daily average	141		110	
σ	12.95		18.96	
R^2	.289		.049	

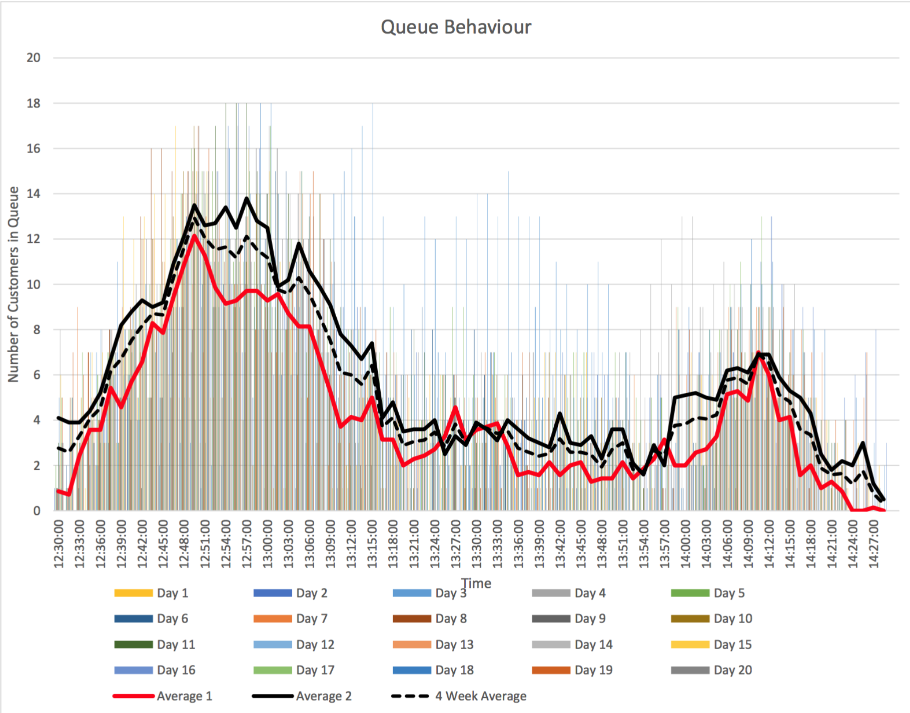

Figure 1: Both Queues

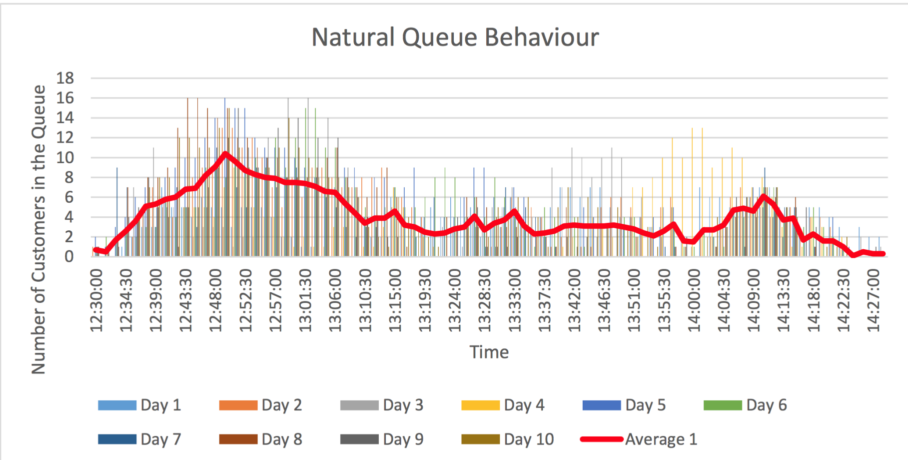

Figure 2: Natural Queue

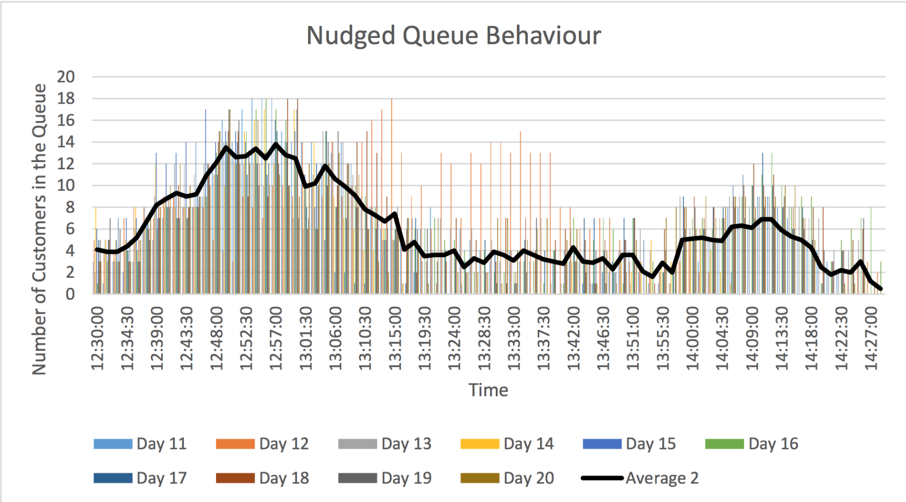

Figure 3: Nudged Queue

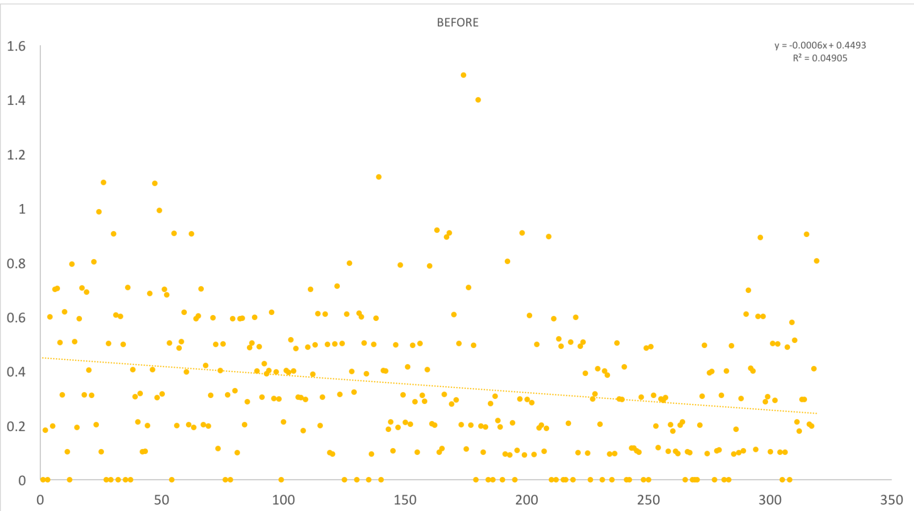

Figure 4: Parameter plot- Before Nudge

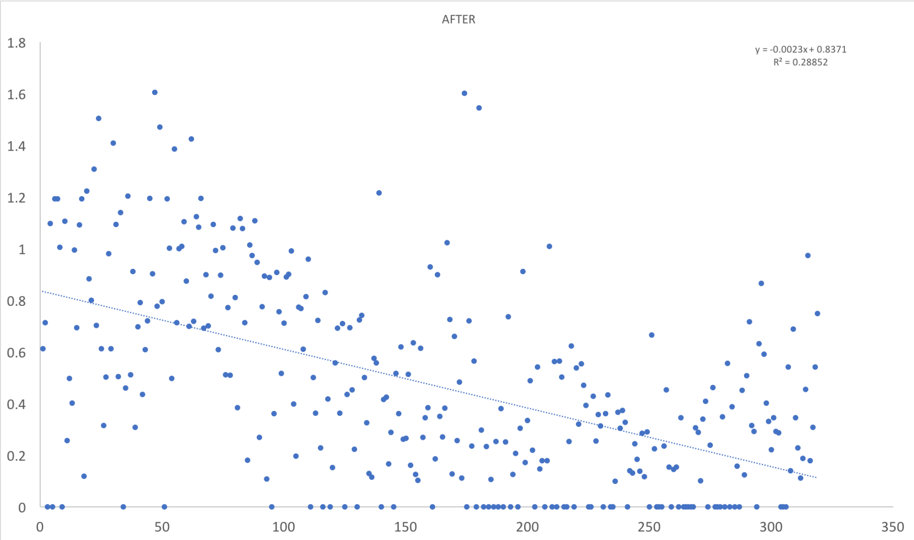

Figure 5: Parameter plot - After Nudge

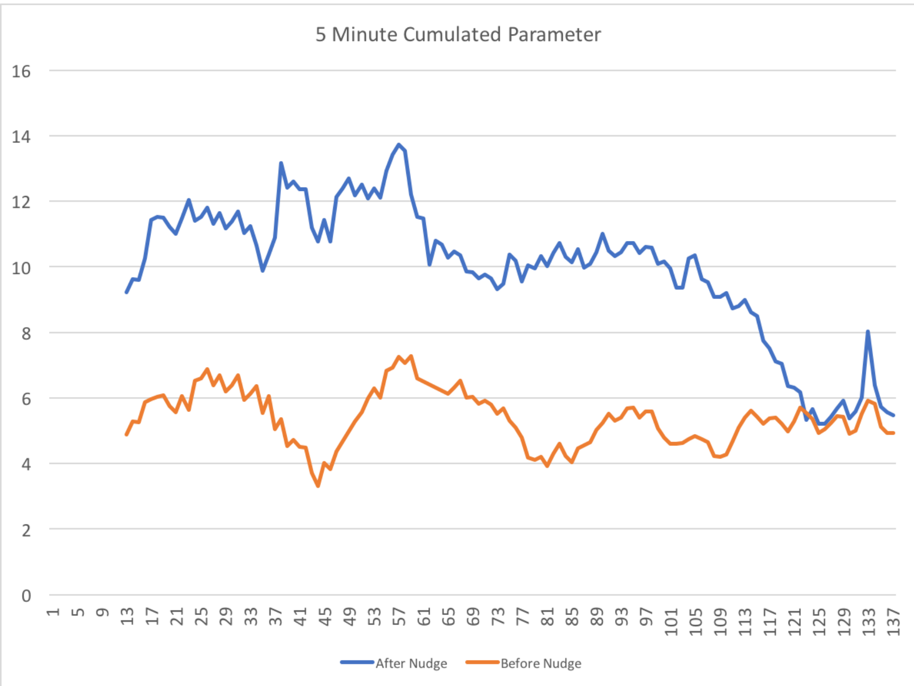

Figure 6: Ffor $T1$

4 Results

In order to interpret the data summary, it is important to remind ourselves of the assumptions of the consumer in Section 1.3. A consumer is loss averse, because of the ambiguity in a laymans forecasted waiting times, they will chose not to join the queue as they will have to forgo the time they would have waited in line to be on time for there appointment (The time constraint - the first assumption).

From the analysis results outlined in Section 3.2, we see a negative regression coefficient of arrivals. This provides evidence that customers become less likely to join the queue. This could have come from 2 reasons, consumers don't have enough time to wait in line or most people queue early into their lunch time. From our assumptions of a person's total cost of consuming a good, the latter reason would imply that their β value would increase with time. Instead of the increasing cost factor being a result of a monotonically decreasing *lunch time* function. However, when we examine the data, we can see that the regression coefficient for Figure 5, is steeper than its counterpart in Figure 4. This would suggest that some customers began queuing earlier. This would imply that the after nudge realised expectation of waiting time was greater than that of before. Causing a *rush* to join the queue as shown by the increased average queue length in Figure 3.

This interpretation leads to a grouping of customers. into those who possess new realised expectations and alter their behaviour depending on whether or not these new expectations are greater or less than before. If they were in line with their previous expectations, their behaviour remains unchanged. This can be seen in the similarities between groups of observations after $T1$, where customers after this time may be in aware of when the peak times occur.

The other group consist of consumers who may have previously been loss averse and may not have previously consumed. This group had higher expected waiting times than their realised expectations with the nudge in place and predominantly appeared in $T1$. They account for majority of increased arrivals per day. (Refer to Table 6 and Figures 4 & 5.) This shows the relationship between a consumers change in propensity to queue as their L_t tends to zero.

The interpretation of the ANOVAs suggests that the choice architecture had been altered in the perception of the consumer, as the difference in groups was accepted to be statistically significant at $\alpha = 1\%$. This was consistent in both metrics. Attention must be payed to the size of the error and low R^2 values. Only a very small proportion of the variance recorded was acheived with the model outlined. This cements the understanding of the variability in human behaviour. Further sighted analysis would be required in order to minimise the error present.

For the initial two weeks a consumer wanting a burrito from Mamas Revenge is presented with a choice architecture of lining up depending on how busy the restaurant is. This depended on the difference in their prior expected waiting time and their *realised* post expectation having seen the queue length and approximated a realised waiting time. This realised waiting time which contains human error in approximation and includes uncertainty, resulted in a maximum queue length of 16, average queue length of 4.01 customers, and an arrival parameter of 0.93 customers/minute. The weeks involving the nudge removed this error in approximation and uncertainty in the consumers mind. This resulted in a maximum queue length of 18, average queue length of 5.91, and arrival parameter of 1.28 customers/minute. Therefore due to this increase in the chosen metrics it is statistically significant to state that uncertainty dictates queuing behaviour with the presence of a time constraint.

5 Discussion

5.1 Limiting factors to conducting the study

i. *Inconvenience of our method of observation*

In order to carry out investigations into the everyday lunch hours of Mamas Revenge, a GoPro needed to be installed. However this method of data collection violated the TCD Research Ethics Checklist Section 1, as it dealt with filming clients without their consent or knowledge. This required qualifying for Section 2 clearance from the School of Social Sciences and Philosophy before the data collection could begin. Initially, the idea was to install the GoPro across the road to check for the number of people joining the queue; however the visualisation of the queue would be obstructed due to traffic.

ii. *Slow collection and processing of data*

The GoPro captured 2 pictures every second, equaling 14,400 pictures and 32 Gb of data per day, totalling 288,000 photos and 640GB of data over the span of 20 days. The GoPro would collect data on a daily basis, taking a total of 20 days of 2 hours equalling 40 hours of data. This would not only hamper the rate of processing the data but also bears the risk of it being rushed. Considerable amounts of time was requred in order to process the data involving; viewing, disregarding and deleting pictures (Roughly 72,000 out of 288,000 pictures). This was due to limitations of the camera software.

iii. *Barriers to more in depth analysis*

Behavioural economics is primarily interested in instances where the standard model is manifestly inadequate or incomplete - and searches for more explanoratory variables to find deterministic relationships. More time would have afforded us the opportunity to explore measuring techniques and investigate of other metrics in order to explore multivariate analysis techniques. This would have allowed groupings of observations into distinguishing types of economic behaviour.

5.2 Limitations of the Study

i *Time constraint of 4 weeks*

It has been clearly shown that 160 hours of data collected was enough time to see a change in human behaviour over time. Whether or not it was enough time to achieve precise and accurate results on the effectiveness of the nudge is another question. A small sample size of 20 days implies a higher variance in the estimated relationship between average number of arrivals and time as is given by $Var(x) = \sum_{i=1}^{n} /SST_x$, where x represents an observation. In other words, the influence of residual errors in the frequency of arrivals per unit time increases due to the small sample size. The time constraint of 4 weeks had a vital role in the presence of inaccuracies in the study. The effectiveness of our nudge was limited by and wholly dependent on the observational skills of the consumers in question. It is reasonable to assume that more clarity might be established if they were to become used to this nudge. Perhaps the limit of our study is that of the limit of a human's ability to change everyday habit. A necessary amount of time is therefore needed for this to be seen.

ii *Lack of subjectivity*

Despite using the GoPro to draw unbiased observations, surveys and interviews should have been carried out in order to compare these two data sets obtained. Subjectivity is still important as were dealing with humans and not *Econs* and hence, would assist in deriving a greater understanding of the cognitive biases involved with humans.

Perhaps if the nudge was presented to a consumer in a hypothetical setting it would present the time constraint to the consumers' conscious decision process, thus removing irrational decision processes and more planning with their consumption timing. When compared to the particular method of nudge observed, the effectiveness of that nudge is down to the observance of the consumers. Possibly the effect would have been clearer if consumers were to become used to the more symmetric knowledge available within the choice architecture. This was not possible to account for in our method of study and time frame.

iii *Environment, seasonality and competition* The week of the 7th -11th November was Reading Week where no lectures take place therfore this week was discounted so as to not to add unnecessary bias to the data with less students at lunch before the nudge was introduced. During the period of observations, Trinity College continuous assesment dealines were approaching which could trigger different behaviour within its main consumer group. Customers may not have minded buying themselves a burrito for lunch as they may have been busy. This would help account for the unexplained variation of the model and a factor of increased arrivals and queue length. Thus acting as a trial week to logistically decide a location for the GoPro, purchase adhesive mounts to attach the GoPro to outside surfaces, become familiar with the GoPro filming, take sample footage, data processing and future calculations that would become required over the next few weeks, as well as to physically demonstrate our idea to staff.

The data included one day with significant rain fall all throughout out observations on that day. This resulted in our lowest recorded daily arrival of 89. The restricted length of observations did not allow us to account for enviromental effects on human behaviour as varying weather conditions have a role to play in the cost of waiting in an uncovered queue.

The model presented in this report, fails to account for the product differentiation of one *i.i.d* restaurant which may account for new additional arrivals.

5.3 Policy and Strategic Reccomendations

The research presented in this project examines relationships between fast food consumer behaviour, queue behaviour and propensity to queue. These have been of broad and sustained interest to producers, advertisers and retailers in recent years. Thus a natural application of this is to provide real time updates for customers in order to increase sales, provide better customer service and adding useful information to the consumer's ever growing available choice architectures due to marketing techniques.

From a policy standpoint, perhaps it could be applied as grounding towards removing uncertainty around the choice architecture of publicly provided goods. This can be interpreted as providing better infrastructure around predictions on waiting times for public transport, conducting similar methods of observations with the intentions of minimising people's dependency on private transport through decreasing the uncertainty and increasing reliabiltiy of public transport. Alternatively, this could be geared towards policy through a more theoretical intent. A parallel may have been drawn betwen our investigation and taxation, by increasing the certainty that people feel they are personally benefiting from paying taxes and their willingness to pay taxes. People have a cost of waiting in line for the sole reason that they are giving up time. People are giving up their time by paying taxes in their income as a result of their forgone time.

6 Conclusion

When considering the effects of expectations as coupled with the total cost of a good under a continuos time Poisson process, it is clear that the removal of uncertainty [2] has had a positive effect on increasing a consumers propensity to queue.

The research presented in this paper shows a relationship between uncertainty and queue behaviour. This was only possible by compensating for the large amounts of variation which was expected. In order to add solidarity to these findings it would be necessary to extend observations over a broader time horizon considering additional variables, such as weather conditions and a breakdown of daily variations. It was set out to observe a relationship of certainty and human behaviour. From observations made, a positive effect was observed with as little error possible within the feasibility constraints.

It has been shown that analysing a queue in a time lapse is an optimal way of measuring human behaviour. This required careful thought on the metrics in which to be studied. However there is room for automation of routines and interpretation with relevant technologies. It was shown that a time period of two weeks is a sufficient amount of time in which a change in human behaviour could be witnessed. The method of nudging/removing uncertainty proved effective to inform consumers of their expected waiting times. Consistent method of analysis were used in order to develop a set of comparative statistics and visualisations in order to interpret a stochastic process.

In addition, a follow up investigation to examine whether the consumers actually accounted for the nudge into their decision before a true conclusion can be drawn. This withstanding, the results of the weeks following the introduction of

[2] Your remaining estimated reading time is 1 minute

the nudge have shown a strong correlation with an increase in queue length and the consumers propensity to queue. This coupled with the economic reasoning of how a consumer gains utility from the certainty of their wait time rather than the difference between their prior & post expectations perhaps indicates that the removal of uncertainty was a factor in their behaviour.

7 References

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