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A Review of Team Member Satisfaction in West Carts

This study was conducted with the intention of determining the overall level of confidence with which each team member performs their job. It asked 57 TM's to fill out a card detailing their job, length of employment, and feelings of value and confidence in their expectations. The results of the study are broken down into 5 parts, based upon the significant results found when analyzing the data. The findings have the ability to inform management decisions and give feedback on management performance. The results can tell which jobs are least aware of what their expectations are, which jobs have higher retention, which jobs feel most appreciated by management, and whether a lunchtime classic has overstayed its welcome.

This paper is broken up into four sections. The first is about the study design. Which questions were asked, to whom were they asked, and when did the study take place will all be answered in section 1. Section 2 is devoted to technical findings, mainly tests of independence and some visual aids. Section 3 is a discussion on the limitations and weaknesses of the study. Finally, Section 4 provides some concluding remarks, taking the statistical analysis and applying it back to West Carts. It identifies problems for leadership to address, as well as areas of success, that are evident in the data. The appendix contains an amendment to the previous paper, "Fun with Stats II".

Study Design

57 West Carts/Pizza Pred team members were surveyed during the week of April 15th-22nd of 2017. Actual survey administration was handled by a few key Team Captains, who asked and assisted TM's to fill out survey cards during down-time. This survey was carried out during one of our peak seasons, and as such, down time was limited. Therefore, most responses come from cashiers, who have more natural interactions with Team Captains. Cooks and Stockers are under-represented in the data, and this does impact the usefulness of the results, *but* any results are better than no results at all, and my sincere gratitude goes out to everyone who helped administer this survey.

This Survey asked 5 Questions:

1. Select Your Job Title
    a. Cashier
    b. Busser
    c. Stocker
    d. Line Cook
2. How long have you worked for Universal?
    a. Write in
3. Do you feel valued at work?
    a. Yes
    b. No
4. Do you feel expectations for you are clearly communicated?
    a. Yes
    b. No

5. Should Cheesy Garlic Pizza be banned from the mini-grill?
   a. Yes
   b. No

72 survey cards were printed and 57 found their way back, filled out. From these 57 none had to be thrown away, though a few did contain incomplete or improper responses. In total, 4 people did not respond with to question 1, 5 people did not respond to question 2, 4 people did not respond to question 3, 6 people did not respond to question 4, and 3 people did not respond to question 5. As opposed to last time, in which I received many cards filled out with "funny" comments instead of answers, this time I received few jokes, and many more serious responses.

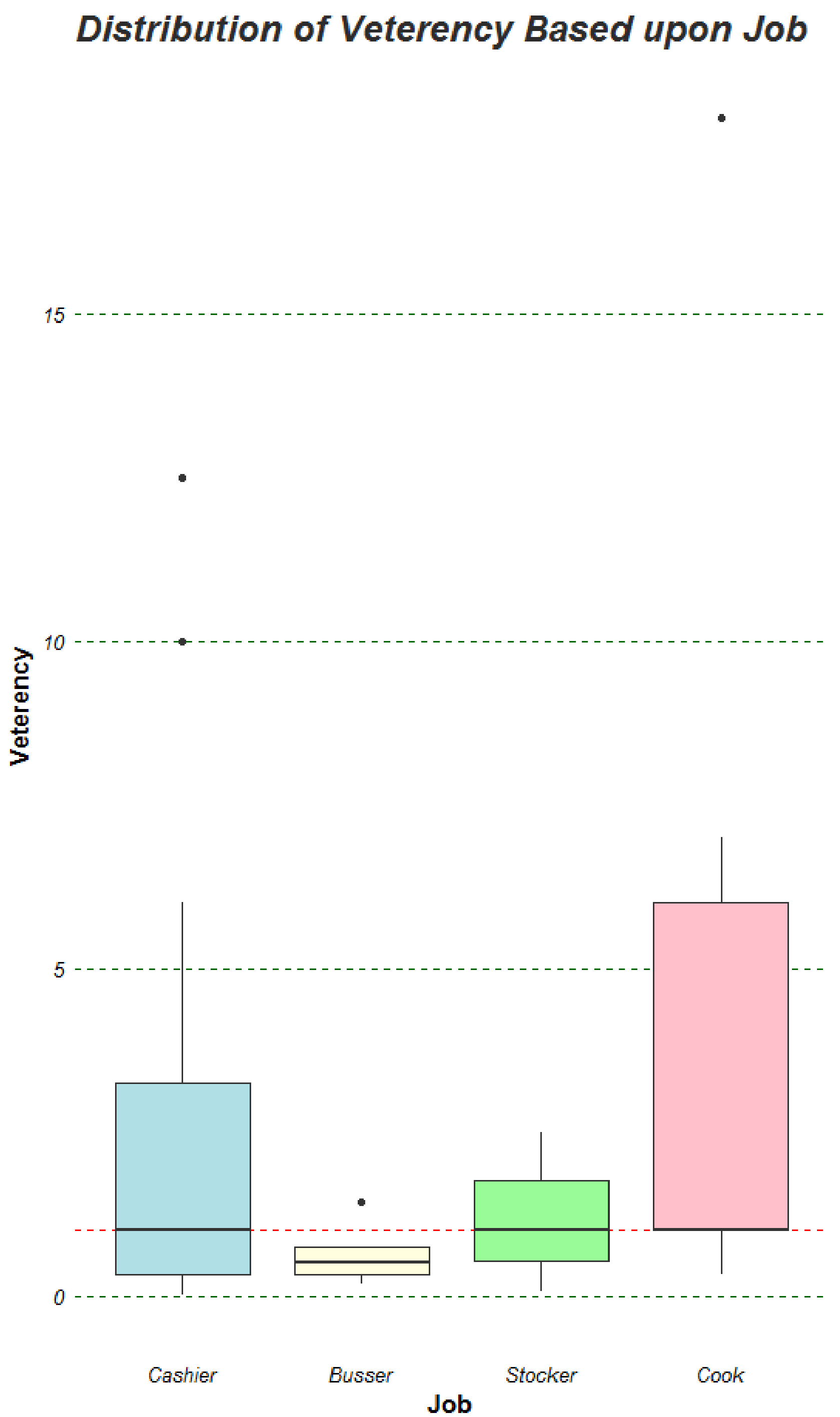
Findings

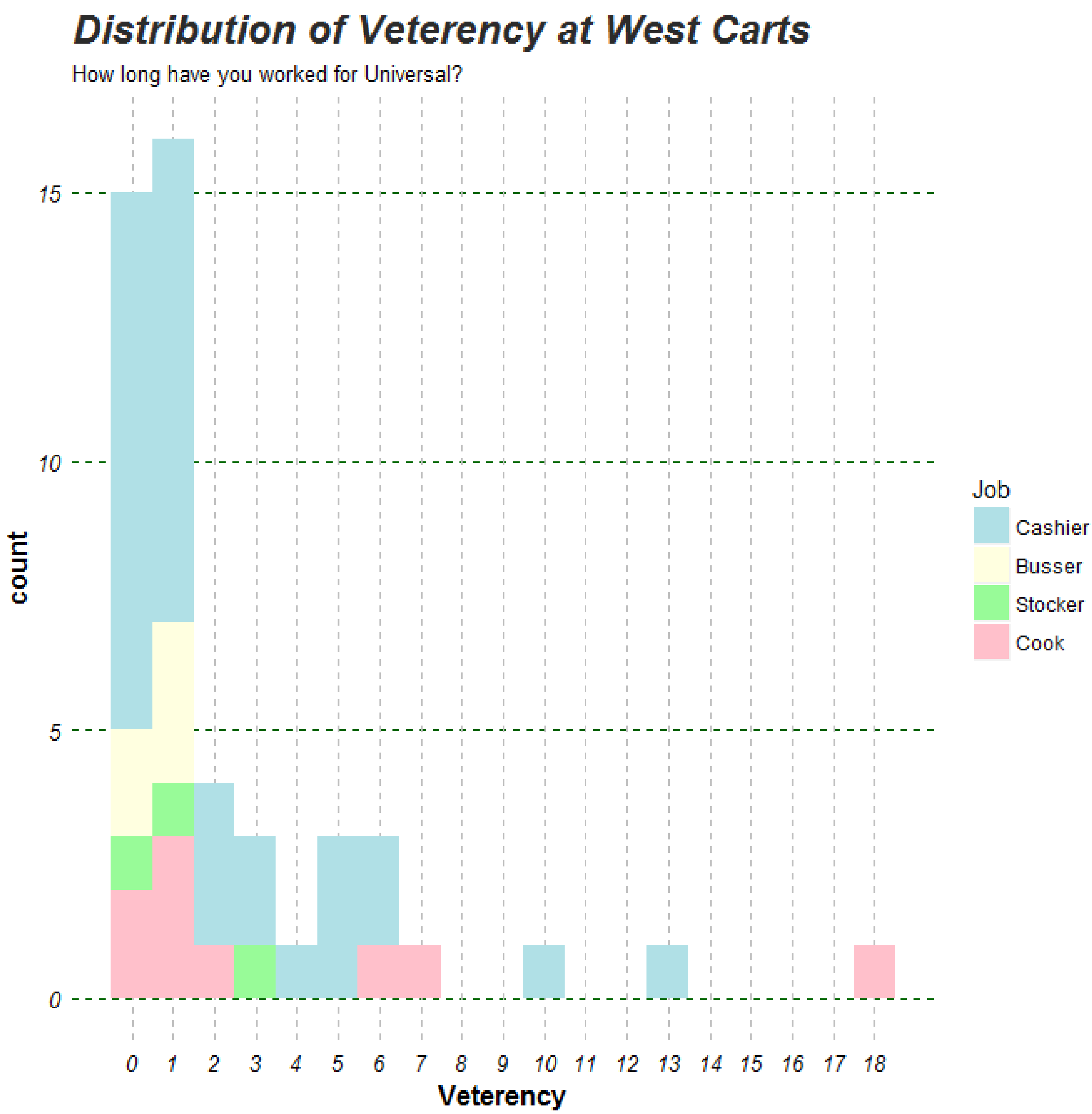
Veterency

Job	Cashier	Busser	Stocker	Cook
Min	4 days	2 months	3 weeks	4 months
Median	**1 year**	**6 months**	**1 year**	**1 year**
Mean	*2 years 4 months*	*6 months*	*1 year 2 months*	*4 years 1 month*
Max	12 years 6 months	1 year 4 months	2 years 6 months	18 years

Table 2.1

Table 2.1 displays the distribution information for employee tenure, broken down by job. Bussers are the newest team members on average, while cooks are the most seasoned (pun intended) team members. There is an obvious outlier in cook dataset, a team member who has worked at Universal for 18 years. Excluding this outlier from the dataset puts the average cook's tenure at 2 years, still on par with cashiers for having the longest stay, on average, at the company. The other note of interest is that the median veterency for team members is all pretty consistent at one year. This implies that half of all team members have been with the company for less than a year, not particularly strong retention. It is likely that this number is inflated by the recent surge in hiring due to volcano bay. If this is indeed the case, then our median tenure is higher than one year, implying stronger retention, though the extent of the shift cannot be known until a future study is conducted. Figures 2.1 and 2.2 below both depict the distributions of veterency among team members. The red bar on figure 1 represents the one year mark, showing the medians for Cooks, Stockers, and Cashiers, as well as the mark to beat for bussers.


Distribution of Veterency Based upon Job
Veterency
15
10
5
0
Cashier
Busser
Stocker
Cook
Job


Distribution of Veterency at West Carts
How long have you worked for Universal?
count
0
5
10
15
Veterency
0 1 2 3 4 5 6 7 8 9 10 11 12 13 14 15 16 17 18
Job
Cashier
Busser
Stocker
Cook

Value

	Yes	No
Cashier	26	8
Busser	5	0
Stocker	1	2
Cook	9	0

Table 2.2

Table 2.2 shows the response to question 2 broken down by Job. 76% of cashiers feel confident in what is expected of them, all cooks and bussers responded in the affirmative. Stockers, on the other hand, responded with 66% of them feeling expectations are not well communicated to them. The first thing to observe here is the miserably small sample size: 3 stockers were asked, out of a population of 15. This is hardly enough to form a real conclusion. For example, observe figure 2.3. This is probability density function for our set of stocker responses. The X-axis displays the true proportion of stockers who feel expectations are clearly communicates. The vertical gold line represents this proportion from our survey. The Y-axis displays the probability of receiving these results at various values of x. As we can see, there is still a chance to get these results with a higher true probability of success. For example, there is a 10% chance of getting only 1 success when the true proportion is 80%. There is still a great deal of uncertainty in the data. Finally, figure 2.4 summarizes the data in a bar plot.

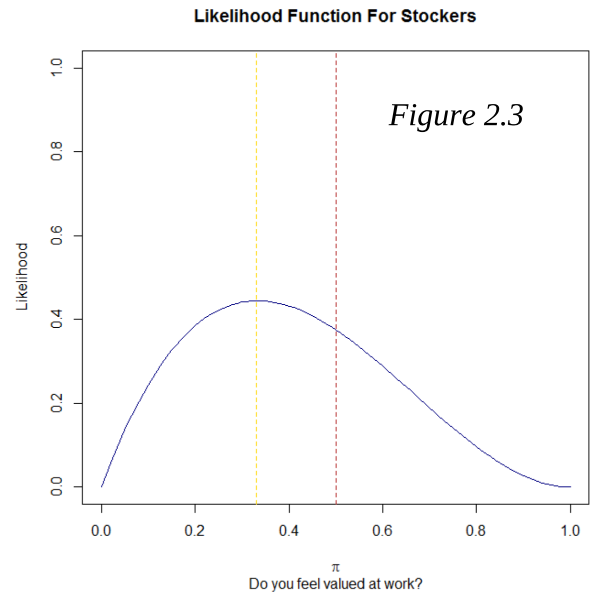


Figure 2.3

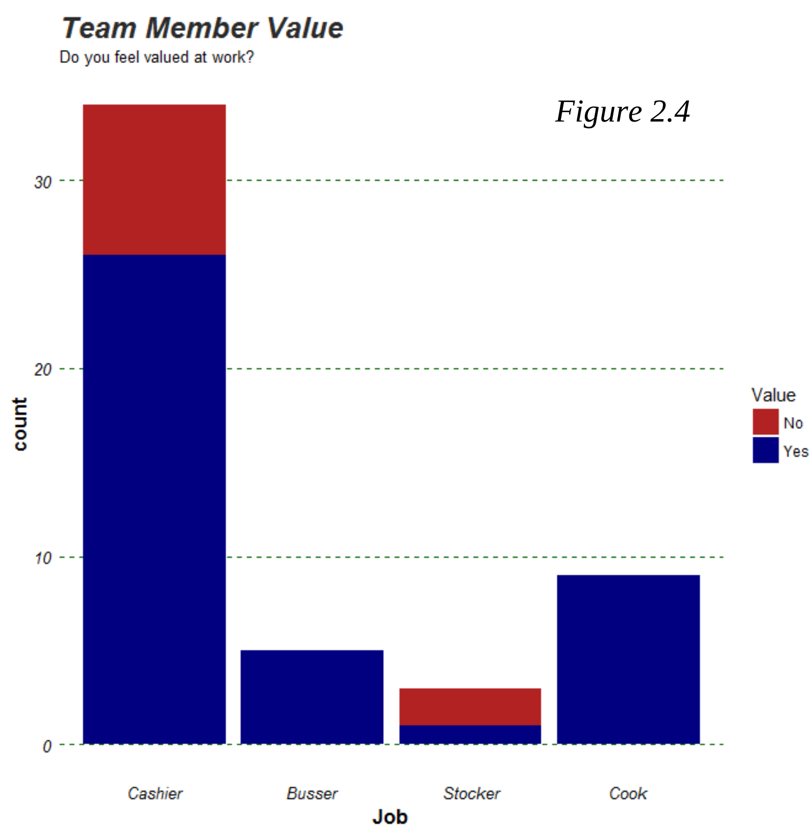


Figure 2.4

Expectations

	Yes	No
Cashier	26	7
Busser	5	0
Stocker	0	2
Cook	8	0

Table 2.3

Table 2.3 shows the response to question 3, about how well team members feel leadership conveys expectations to them. These responses are not very variable, with bussers and cooks all feeling confident in their understanding of the expectations upon them. Cashiers responded with 78% in the affirmative, while stockers responded wholly in the negative. Again, the reason for this is likely due to sample size. Two people are not enough to speak for the whole team. Again, looking at the probability density function, there is a 25% chance of receiving zero positive responses when the true proportion is 50%. Figure 2.5 details the results in a bar plot.

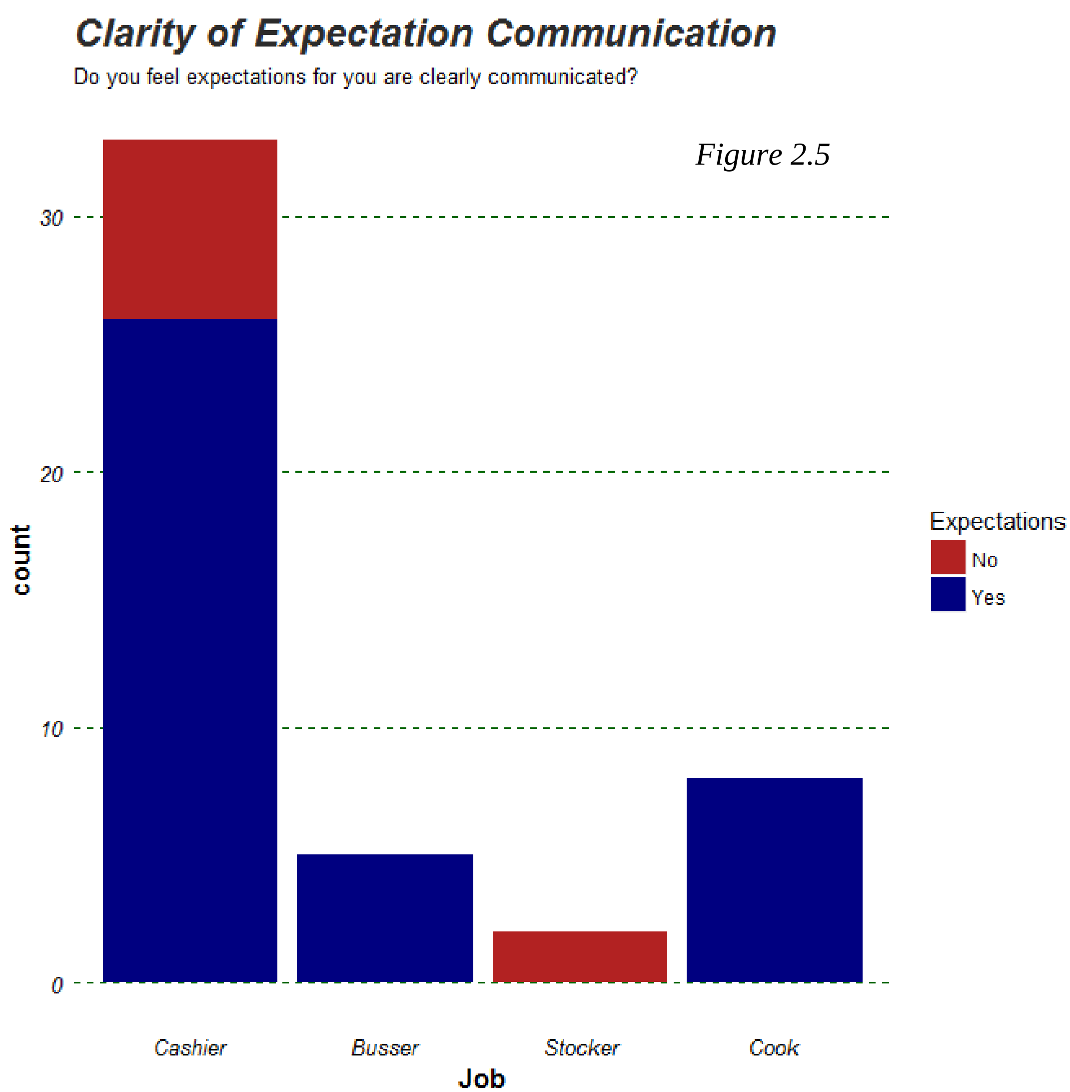


Figure 2.5

Cheesy Garlic Pizza

	Yes	No
Cashier	7	28
Busser	2	3
Stocker	0	2
Cook	2	6

Table 2.4

Table 2.4 details responses to question 5, asking whether Cheesy Garlic Pizza ought to be banned from the mini-grill. Performing a Pearson's χ^2 test of independence on this table gives a p-value of 0.6522, not low enough for us to reject the null hypothesis of independence. Therefore, it's not prudent to display the results broken down by job. The resulting table 2.5 shows that 78% of respondents are in favor of keeping Cheesy Garlic Pizza in the Mini-Grill.

Yes, Ban It	No, Keep It
22%	78%

Table 2.5

Figure 2.6 displays the count data for this question.

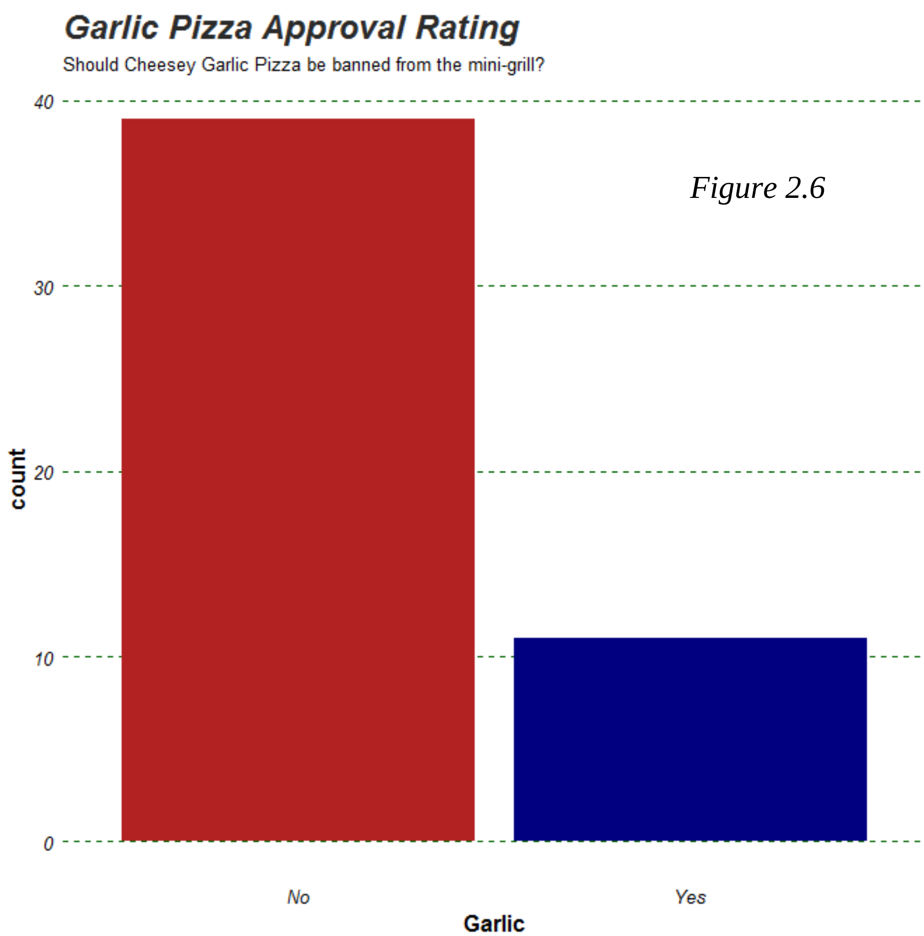


Figure 2.6

Values ~ Expectations

Value / Expectations	Yes	No	Total
Yes	37	3	40
No	2	8	10
Total	39	11	**50**

Table 2.6

Table 2.6 contains the responses to questions 3 & 4, showing the relationship between clear communication of expectations and a feeling of value. Running a Pearson's χ^2 test on this table gives a p-value ≈ 0, allowing us to handily reject the null hypothesis of independence and conclude that there is a relationship between the two. The next step is to fit a model. Seeing as we are modeling two binomial responses, a logit model was selected as the most appropriate. The resulting fit is:

$$\log\left(\frac{\pi}{1-\pi}\right) = -0.9808 + 3.986 Expectations$$

Where Expectations = 1 if expectations have been clearly communicated, and 0 if not.

This model has a low AIC and a significant coefficient, leading us to believe that it is a strong fit for the data. Figure 2.7 represents this fit. From it, we can see the steadily increasing probability of a team member feeling valued as the probability of expectations being clearly communicate increases. Specifically, when expectations have not been clearly communicated (i.e. Expectations = 0), the probability of a team member feeling values is equal to 27%. When the opposite is true, a team member has a 94% chance of feeling valued.

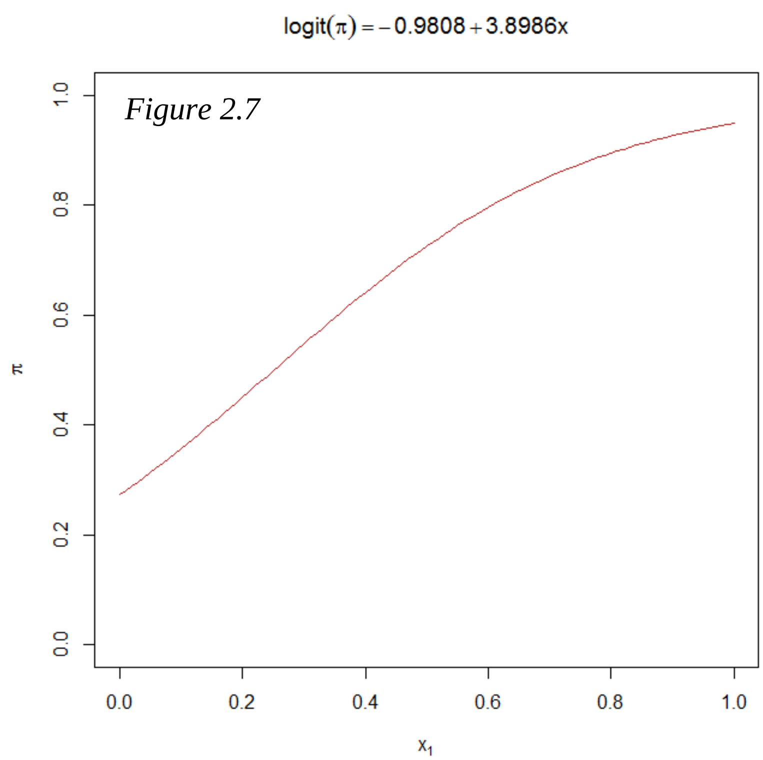
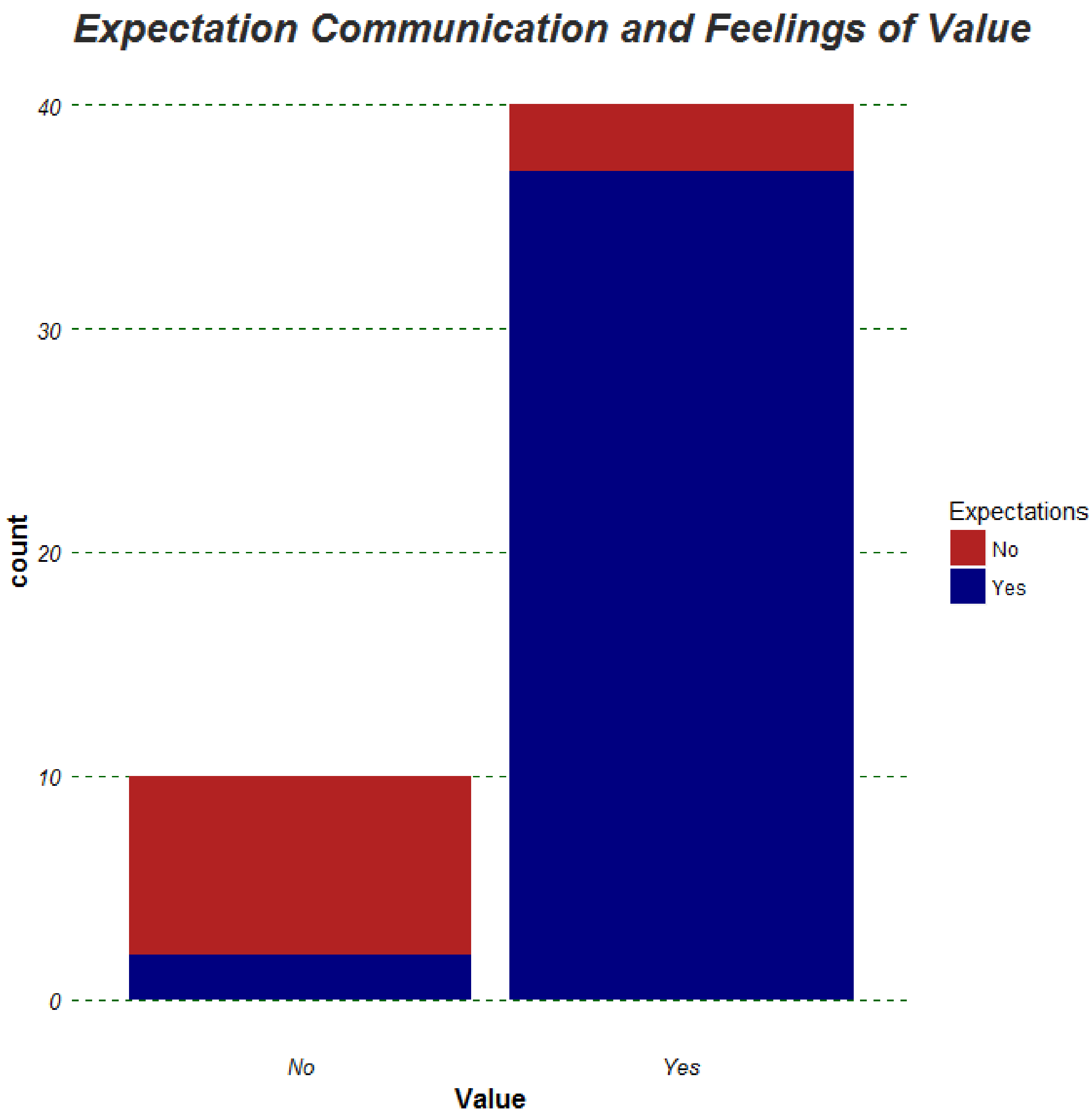


Figure 2.7

Figure 2.8 displays the count data. The relationship should still be abundantly clear.

Figure 2.8


Expectation Communication and Feelings of Value
count
40
30
20
10
0
No
Yes
Value
Expectations
No
Yes

Limitations

The greatest limitation of this study is its lack of representation for cooks and stockers. While bussers and cashiers are incredibly well represented, the study would have benefited from a more robust sample pool. The second limitation was in its design. Question 4 (Do you feel expectations for you are clearly communicated) can be easily confused with “Do you know what your job is?”, a question much easier to answer yes to (hopefully). A better question would have been “Do you feel expectations put upon you are appropriate?”. This question implies the previous and gets the added benefit of telling us whether team members believe we expect too much or too little. The final limitation was in administration. Asking team members to rate the performance of leadership is probably best done without leadership standing right next to you. I am not upset that high proportions of team members feel valued, but I do believe in cautious optimism. The numbers are good, but there are confounding factors that might have made them better than they ought to be.

Conclusion

This study identified that bussers have the lowest retention of all jobs, with cooks and cashiers both tying for highest (after removing a significant outlier). It found that team members overwhelmingly feel valued and feel as though expectations for them are clearly communicated. The exception is the stockers, although the stocker sample size is too low for a definitive conclusion. Stockers sampled both feel under-valued and as though expectations for them are not clearly communicated. The venue has already begun to roll out stocker incentives, including perfect cart ballots and perfect open/close incentives – both of which should increase the stockers feeling valued if they are successfully and consistently implemented. Communication is the next problem. Standards for stocking are all over the place, and need to be centralized. Leadership needs to come to a consensus as far as what appropriate standards are for stockers, and stockers need to be made aware of this standard, preferably all at the same time, in some kind of meeting with all the stockers. I wonder what we could call it? An every stocker meeting? A stocker all meeting? Something like that.

The next conclusion of this paper is the salvation of cheesy garlic pizza. I was really hoping this would be the next Brexit but people seem to have fairly strong convictions about garlic. Finally, this paper established the relationship between clear communication of expectations and the recipient’s feeling valued. Specifically, that the difference between clearly communicating expectations and not causes a 67% increase in the probability that a team member will feel valued. This is a massive increase for something that takes such little effort.

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Appendix A: Amendment to "Fun with Stats II"

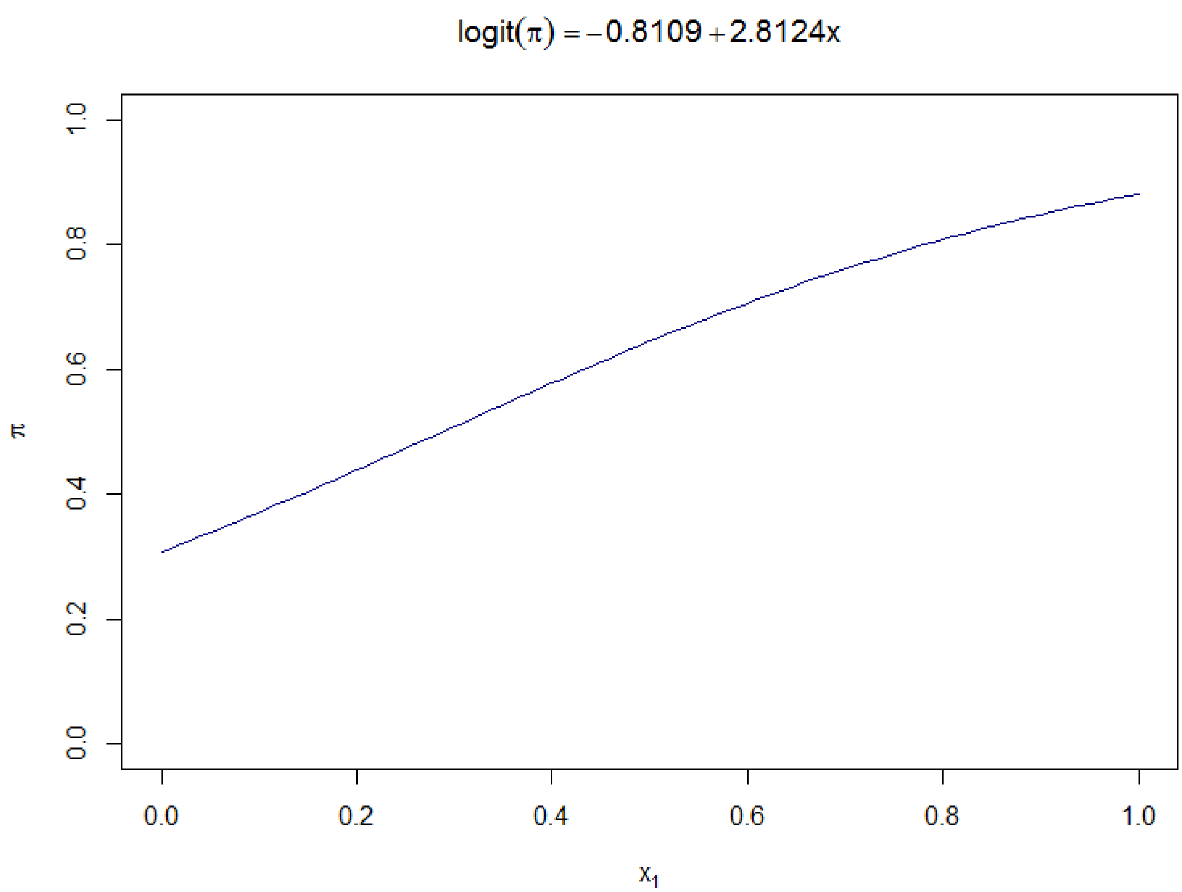
Enjoy – Trained Logit Model

In the previous edition, I attempted to fit a logit model to explain the relationship between feeling well trained and enjoying work. My attempts failed, to my frustration, when R would only give me models that used 1 to predict 1. Meaning that my only coefficient was 1. It was dumb. But I discovered that by adding the `weights` argument to my code, I could successfully write a model.

$$\log\left(\frac{\pi}{1-\pi}\right) = -0.8109 + 2.8124 TrainedYes$$

Where TrainedYes = 1 if the employee feels well trained and 0 otherwise.

This model has a significant coefficient and a low AIC, meaning we feel that this model fits fairly well. Figure A.1 is the curve given by the model. Observing the curve, we can see than an employee has a 30% chance of enjoying work if they don't feel well trained but has an 88% chance of enjoying work is they feel well trained. This is a significant increase and represents the importance of training to morale.



Appendix B: R Output

```
> setwd("D:/Files/Programing and Data/R Directory/Work Surveys")
>
> library(ggplot2)
Warning message:
package 'ggplot2' was built under R version 3.3.2
>
> ############################################################
> #                                                          #
> #  ##### #   # #   #         #       # ##### ##### #   #   #
> #  #     #   # ##  #         #       #   #     #   #   #   #
> #  ####  #   # # # #         #   #   #   #     #   #####   #
> #  #     #   # #  ##         #  # #  #   #     #   #   #   #
> #  #      ###  #   #          ##   ##  #####   #   #   #   #
> #                                                          #
> #  ###  #########     #      #########  ###    #########   #
> # #   #     #        # #         #     #   #    #  #  #    #
> # #         #       #   #        #     #        #  #  #    #
> #  ###      #      #     #       #      ###     #  #  #    #
> #     #     #     #########      #         #    #  #  #    #
> # #   #     #    #         #     #     #   #    #  #  #    #
> #  ###      #   #           #    #      ###    #########   #
> #                                                          #
> ############################################################
>
> fws <- read.csv('fws3.csv')
> head(fws)
  Job Veterency Value Expectations Garlic
1   2      1.00     0            0      0
2   0      1.00     0            0      0
3   0      0.67     1            1      0
4   0      0.08     1            1      0
5   3      7.00     1            1     NA
6   1      0.33     1            1      0
> summary(fws)
      Job           Veterency           Value          Expectations
 Min.   :0.000   Min.   : 0.0100   Min.   :0.0000   Min.   :0.0000
 1st Qu.:0.000   1st Qu.: 0.3975   1st Qu.:1.0000   1st Qu.:1.0000
 Median :0.000   Median : 1.0000   Median :1.0000   Median :1.0000
 Mean   :0.717   Mean   : 2.4254   Mean   :0.7925   Mean   :0.7843
 3rd Qu.:1.000   3rd Qu.: 3.0000   3rd Qu.:1.0000   3rd Qu.:1.0000
 Max.   :3.000   Max.   :18.0000   Max.   :1.0000   Max.   :1.0000
 NA's   :4       NA's   :5         NA's   :4        NA's   :6
     Garlic
 Min.   :0.0000
 1st Qu.:0.0000
 Median :0.0000
 Mean   :0.2593
 3rd Qu.:0.7500
 Max.   :1.0000
 NA's   :3
```

```
> ## Survey Asked 5 Questions
> ### 1. What is Your Job?
> #### JOB
> ### 2. How long have you worked at univesal
> #### VETERENCY
> ### 3. Do you feel valued at work
> #### VALUE
> ### 4. Do you feel expectations for you are clearly communicated
> #### EXPECTATIONS
> ### 5. Should cheesey garlic pizza be banned from the minigrill
> #### GARLIC
>
> ## From this I want to examine 8 relationships
> ### 1. Veterency ~ Job
> ### 2. Expectations ~ Job
> ### 3. Value ~ Job
> ### 4. Garlic ~ Job
> ### 5. Value ~ Veterency
> ### 6. Expectations ~ Veterency
> ### 7. Garlic ~ Veterency
> ### 8. Value ~ Expectations
>
> ## To rephrase in terms of questions
> ### Q1
> #### 4 as Predictor
> #### 0 as Response
> ### Q2
> #### 3 as Predictor
> #### 1 as Response
> ### Q3
> #### 2 as Predictor
> #### 1 as Response
> ### Q4
> #### 1 as Predictor
> #### 2 as Response
> ### Q5
> #### 0 as Predictor
> #### 2 as Response
>
> #################################
> ## PART A: Global Deffinitions ##
> #################################
> j.names <- c('Cashier', 'Busser', 'Stocker', 'Line Cook')
>
> westcarts_theme <- theme(
+  plot.title = element_text(face = 'bold.italic', size = '18', color = 'gray17'),
+  axis.title = element_text(face = 'bold', size = '12', color = 'black'),
+  axis.text = element_text(face = 'italic', size = '10', color = 'black'),
+  axis.ticks = element_blank(),
+  panel.background = element_rect(fill = 'white', color = 'white'),
+  panel.grid.major.x = element_blank(),
+  panel.grid.major.y = element_line(linetype = 2, color = 'darkgreen'),
+  panel.grid.minor.x = element_blank(),
```

```
+  panel.grid.minor.y = element_blank()
+  )
>
> ############################
> ## PART 1: Veterency ~ Job ##
> ############################
> # First we examine the means
> c.data <- fws[which(fws$Job == 0),]                 # Filter out Cashiers
> c.vet.clean <- c.data[complete.cases(c.data[,2]),]  # Ditch the NA's
> c.vet.mean <- mean(c.vet.clean$Veterency)           # Calculate a Mean
>                                                     # Repeat
> b.data <- fws[which(fws$Job == 1),]
> b.vet.clean <- b.data[complete.cases(b.data[,2]),]
> b.vet.mean <- mean(b.vet.clean$Veterency)
>
> s.data <- fws[which(fws$Job == 2),]
> s.vet.clean <- s.data[complete.cases(s.data[,2]),]
> s.vet.mean <- mean(s.vet.clean$Veterency)
>
> l.data <- fws[which(fws$Job == 3),]
> l.vet.clean <- l.data[complete.cases(l.data[,2]),]
> l.vet.mean <- mean(l.vet.clean$Veterency)
>
> j.vet.means <- c(c.vet.mean, b.vet.mean, s.vet.mean, l.vet.mean)
> means.comp <- data.frame(j.names, j.vet.means)
> #--------#
> means.comp
    j.names j.vet.means
1   Cashier    2.311562
2    Busser    0.634000
3   Stocker    1.186667
4 Line Cook    4.083333
> #--------#
>
> # Now lets model
> jobsvet.clean <- fws[complete.cases(fws[,1:2]),]
> jobs.vet <- data.frame(C = c(1:49),
+  B = c(1:49),
+  S = c(1:49),
+  L = c(1:49))
> jobs.vet[1] <- ifelse(jobsvet.clean[1] == 0, 1, 0)
> jobs.vet[2] <- ifelse(jobsvet.clean[1] == 1, 1, 0)
> jobs.vet[3] <- ifelse(jobsvet.clean[1] == 2, 1, 0)
> jobs.vet[4] <- ifelse(jobsvet.clean[1] == 3, 1, 0)
> jobs.vet[5] <- jobsvet.clean[2]
> colnames(jobs.vet) <- c('JobCashier', 'JobBusser', 'JobStocker', 'JobCook', 'Vet')
> jobvet.fit <- lm(Vet ~ JobCashier + JobBusser + JobStocker + JobCook, data = jobs.vet)
> summary(jobvet.fit)

Call:
lm(formula = Vet ~ JobCashier + JobBusser + JobStocker + JobCook,
    data = jobs.vet)
```

```
Residuals:
   Min     1Q Median     3Q    Max 
-3.753 -2.083 -1.127  0.786 13.917 

Coefficients: (1 not defined because of singularities)
            Estimate Std. Error t value Pr(>|t|)   
(Intercept)    4.083      1.164   3.507  0.00104 **
JobCashier    -1.772      1.318  -1.345  0.18551   
JobBusser     -3.449      1.948  -1.771  0.08339 . 
JobStocker    -2.897      2.328  -1.244  0.21991   
JobCook           NA         NA      NA       NA   
---
Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1

Residual standard error: 3.493 on 45 degrees of freedom
Multiple R-squared:  0.07696,	Adjusted R-squared:  0.01542 
F-statistic: 1.251 on 3 and 45 DF,  p-value: 0.3027

> # this model is terrible
> # Lets make a box and whisker plot
> jobs.graph <- jobsvet.clean[,1:2]
> jobs.graph[1] <- as.factor(jobs.graph$Job)
> 
> ggplot(jobs.graph, aes(x = Job, y = Veterency, fill = Job)) +
+ scale_x_discrete(labels = c('Cashier', 'Busser', 'Stocker', 'Cook')) +
+ scale_fill_manual(values = c('powderblue', 'lightyellow', 'palegreen', 'pink'),
+ name = 'Job', labels = c('Cashier', 'Busser', 'Stocker', 'Cook')) +
+ geom_hline(aes(yintercept=1), linetype = 2, color = 'red') +
+ guides(fill = FALSE) +
+ geom_boxplot() + labs(title = 'Distribution of Veterency Based upon Job') +
+ westcarts_theme
> 
> ggplot(jobs.graph, aes(x = Veterency, fill = Job)) + geom_histogram(bins = 19) +
+ scale_fill_manual(values = c('powderblue', 'lightyellow', 'palegreen', 'pink'),
+ name = 'Job', labels = c('Cashier', 'Busser', 'Stocker', 'Cook')) +
+ scale_x_continuous(breaks = c(0:18)) +
+ labs(title = 'Distribution of Veterency at West Carts',
+      subtitle = 'How long have you worked for Universal?') +
+ westcarts_theme + theme(panel.grid.major.x = element_line(linetype = 2, color = 
'grey75'))
> 
> ################################
> ## PART 2: Expectations ~ Job ##
> ################################
> # First we construct a table
> j.ex.clean <- fws[complete.cases(fws[,c(1,4)]),]                  # Filter out NA's
> j.ex.table <- xtabs(~Job + Expectations, data = j.ex.clean)       # Create a Table
> colnames(j.ex.table) <- c('No', 'Yes')                            # Rename Columns
> rownames(j.ex.table) <- c('Cashier', 'Busser', 'Stocker', 'Cook')  # Rename Rows
> #--------#
> j.ex.table
         Expectations
Job        No Yes
```

```
  Cashier  7  26
  Busser   0   5
  Stocker  2   0
  Cook     0   8
> #--------#
> chisq.test(j.ex.table, correct = FALSE)                           # Dependant

        Pearson's Chi-squared test

data:  j.ex.table
X-squared = 11.798, df = 3, p-value = 0.008108

Warning message:
In chisq.test(j.ex.table, correct = FALSE) :
  Chi-squared approximation may be incorrect
> fisher.test(j.ex.table)                                           # Dependant

        Fisher's Exact Test for Count Data

data:  j.ex.table
p-value = 0.02564
alternative hypothesis: two.sided

> # Cashiers are the only ones that vary
> j.ex.ptable <- j.ex.table / rowSums(j.ex.table)
> #---------#
> j.ex.ptable
         Expectations
Job              No       Yes
  Cashier 0.2121212 0.7878788
  Busser  0.0000000 1.0000000
  Stocker 1.0000000 0.0000000
  Cook    0.0000000 1.0000000
> #---------#
>
> curve(dbinom(0,2,x), xlim = c(0,1), ylim = c(0,1),
+ main = 'Likelihood Function For Stockers',
+ sub = 'Do you feel expectations for you are clearly communicated?',
+ xlab = expression(pi), ylab = 'Likelihood', col = 'navy')
> abline(v = 0.25, lty = 'dashed', col = 'firebrick')
> abline(v = 0, lty = 'dashed', col = 'gold')
>
> ex.graph <- j.ex.clean[,c(1,4)]
> ex.graph[1] <- as.factor(ex.graph$Job)
> ex.graph[2] <- as.factor(ex.graph$Expectations)
> ex.graph[2] <- ifelse(ex.graph[2] == 1, 'Yes', 'No')
>
> ggplot(ex.graph, aes(x = Job, fill = Expectations)) +  geom_bar() +
+ labs(title = 'Clarity of Expectation Communication',
+      subtitle = 'Do you feel expectations for you are clearly communicated?') +
+ scale_fill_manual(values = c('firebrick', 'navy'))+
+ scale_x_discrete(labels = c('Cashier', 'Busser', 'Stocker', 'Cook')) +
+ westcarts_theme
```

```
>
> ########################
> ## PART 3: Value ~ Job ##
> ########################
> j.value.clean <- fws[complete.cases(fws[,c(1,3)]),]                       # Filter out NA's
> j.value.table <- xtabs(~Job + Value, data = j.value.clean)                # Construct table
> colnames(j.value.table) <- c('No', 'Yes')                                 # Rename Columns
> rownames(j.value.table) <- c('Cashier', 'Busser', 'Stocker', 'Cook')   # Rename Rows
> #-----------#
> j.value.table
         Value
Job       No Yes
  Cashier  8  26
  Busser   0   5
  Stocker  2   1
  Cook     0   9
> #-----------#
> chisq.test(j.value.table, correct = FALSE)                                 # Dependant

        Pearson's Chi-squared test

data:  j.value.table
X-squared = 7.961, df = 3, p-value = 0.04683

Warning message:
In chisq.test(j.value.table, correct = FALSE) :
  Chi-squared approximation may be incorrect
> fisher.test(j.value.table)                                                 # Dependant

        Fisher's Exact Test for Count Data

data:  j.value.table
p-value = 0.05392
alternative hypothesis: two.sided

> # Stockers and Cashierss both Vary
> # stockers is easy math
> # 2/3rds feel not valued
> j.value.ptable <- j.value.table / rowSums(j.value.table)
> #------------#
> j.value.ptable
         Value
Job              No       Yes
  Cashier 0.2352941 0.7647059
  Busser  0.0000000 1.0000000
  Stocker 0.6666667 0.3333333
  Cook    0.0000000 1.0000000
> #------------#
>
> curve(dbinom(1,3,x), xlim = c(0,1), ylim = c(0,1),
+ main = 'Likelihood Function For Stockers',
+ sub = 'Do you feel valued at work?',
+ xlab = expression(pi), ylab = 'Likelihood', col = 'navy')
```

```
> abline(v = 0.33, lty = 'dashed', col = 'firebrick')
>
>
>
> value.graph <- j.value.clean[,c(1,3)]
> value.graph[1] <- as.factor(value.graph$Job)
> value.graph[2] <- as.factor(value.graph$Value)
> value.graph[2] <- ifelse(value.graph[2] == 1, 'Yes', 'No')
>
> ggplot(value.graph, aes(x = Job, fill = Value)) +  geom_bar() +
+ labs(title = 'Team Member Value',
+      subtitle = 'Do you feel valued at work?') +
+ scale_fill_manual(values = c('firebrick', 'navy'))+
+ scale_x_discrete(labels = c('Cashier', 'Busser', 'Stocker', 'Cook')) +
+ westcarts_theme
>
> #########################
> ## PART 4: Garlic ~ Job ##
> #########################
> j.gar.clean <- fws[complete.cases(fws[,c(1,5)]),]
> j.gar.table <- xtabs(~Job + Garlic, data = j.gar.clean)
> colnames(j.gar.table) <- c('No', 'Yes')
> rownames(j.gar.table) <- c('Cashier', 'Busser', 'Stocker', 'Cook')
> #---------#
> j.gar.table
         Garlic
Job        No Yes
  Cashier 28   7
  Busser   3   2
  Stocker  2   0
  Cook     6   2
> #---------#
> j.gar.ptable <- j.gar.table / rowSums(j.gar.table)
> #----------#
> j.gar.ptable
         Garlic
Job          No  Yes
  Cashier 0.80 0.20
  Busser  0.60 0.40
  Stocker 1.00 0.00
  Cook    0.75 0.25
> #----------#
>
> chisq.test(j.gar.table, correct = FALSE)

        Pearson's Chi-squared test

data:  j.gar.table
X-squared = 1.6317, df = 3, p-value = 0.6522

Warning message:
In chisq.test(j.gar.table, correct = FALSE) :
  Chi-squared approximation may be incorrect
```

```
> fisher.test(j.gar.table)

        Fisher's Exact Test for Count Data

data:  j.gar.table
p-value = 0.7833
alternative hypothesis: two.sided

>
> # Independance means I can condense into:
> garlic.props <- colSums(j.gar.table) / sum(j.gar.table)
> #----------#
> garlic.props
  No  Yes
0.78 0.22
> #----------#
>
> gar.graph <- j.gar.clean[,c(1,5)]
> gar.graph[1] <- as.factor(gar.graph$Job)
> gar.graph[2] <- as.factor(gar.graph$Garlic)
> gar.graph[2] <- ifelse(gar.graph[2] == 1, 'Yes', 'No')
>
> ggplot(gar.graph, aes(x = Garlic)) +  geom_bar(fill = c('firebrick', 'navy')) +
+ labs(title = 'Garlic Pizza Approval Rating',
+      subtitle = 'Should Cheesey Garlic Pizza be banned from the mini-grill?') +
+ westcarts_theme
>
> ###############################
> ## PART 5: Veterency ~ Value ##
> ###############################
> vv.clean <- fws[complete.cases(fws[,c(2,3)]),]
> vv.fit <- glm(Value ~ Veterency, family = binomial(link = logit), data = vv.clean)
> summary(vv.fit)

Call:
glm(formula = Value ~ Veterency, family = binomial(link = logit),
    data = vv.clean)

Deviance Residuals:
    Min       1Q   Median       3Q      Max
-1.9022   0.3999   0.6521   0.7146   0.7395

Coefficients:
            Estimate Std. Error z value Pr(>|z|)
(Intercept)   1.1551     0.4634   2.493   0.0127 *
Veterency     0.1901     0.1999   0.951   0.3416
---
Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1

(Dispersion parameter for binomial family taken to be 1)

    Null deviance: 46.738  on 48  degrees of freedom
Residual deviance: 45.327  on 47  degrees of freedom
```

```
AIC: 49.327

Number of Fisher Scoring iterations: 5

> # Veterency does not have a substantial effect on feeling valued
>
> ######################################
> ## PART 6: Veterency ~ Expectations ##
> ######################################
> ve.clean <- fws[complete.cases(fws[,c(2,4)]),]
> ve.fit <- glm(Expectations ~ Veterency, family = binomial(link = logit), data =
+ ve.clean)
> summary(ve.fit)

Call:
glm(formula = Expectations ~ Veterency, family = binomial(link = logit),
    data = ve.clean)

Deviance Residuals:
    Min       1Q   Median       3Q      Max
-1.8470   0.2520   0.6531   0.7635   0.8027

Coefficients:
            Estimate Std. Error z value Pr(>|z|)
(Intercept)   0.9647     0.4752   2.030   0.0424 *
Veterency     0.2702     0.2382   1.134   0.2566
---
Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1

(Dispersion parameter for binomial family taken to be 1)

    Null deviance: 45.477  on 45  degrees of freedom
Residual deviance: 43.203  on 44  degrees of freedom
AIC: 47.203

Number of Fisher Scoring iterations: 6

> # Veterency does not have a substantial effect on Expectations
>
> ################################
> ## PART 7: Veterency ~ Garlic ##
> ################################
> vg.clean <- fws[complete.cases(fws[,c(2,5)]),]
> vg.fit <- glm(Garlic ~ Veterency, family = binomial(link = logit), data = vg.clean)
> summary(vg.fit)

Call:
glm(formula = Garlic ~ Veterency, family = binomial(link = logit),
    data = vg.clean)

Deviance Residuals:
    Min       1Q   Median       3Q      Max
-0.7788  -0.7627  -0.7305  -0.4432   1.8582
```

```
Coefficients:
            Estimate Std. Error z value Pr(>|z|)
(Intercept) -1.03676    0.42062  -2.465   0.0137 *
Veterency   -0.09876    0.13546  -0.729   0.4659
---
Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1

(Dispersion parameter for binomial family taken to be 1)

    Null deviance: 52.188  on 48  degrees of freedom
Residual deviance: 51.521  on 47  degrees of freedom
AIC: 55.521

Number of Fisher Scoring iterations: 4

> # Veterency does not have a substantial effect on love of garlic pizza
>
> ###################################
> ## PART 8: Valued ~ Expectations ##
> ###################################
> ev.clean <- fws[complete.cases(fws[,c(3,4)]),]
> ev.table <- xtabs(~Value + Expectations, data = ev.clean)
> rownames(ev.table) <- c('No', 'Yes')
> colnames(ev.table) <- c('No', 'Yes')
> #------#
> ev.table
     Expectations
Value No Yes
  No   8   2
  Yes  3  37
> #------#
> chisq.test(ev.table, correct = FALSE)

        Pearson's Chi-squared test

data:  ev.table
X-squared = 24.505, df = 1, p-value = 7.413e-07

Warning message:
In chisq.test(ev.table, correct = FALSE) :
  Chi-squared approximation may be incorrect
> fisher.test(ev.table)

        Fisher's Exact Test for Count Data

data:  ev.table
p-value = 1.211e-05
alternative hypothesis: true odds ratio is not equal to 1
95 percent confidence interval:
   5.493803 590.484594
sample estimates:
odds ratio
```

```
  41.80906

>
> ev.fit <- glm(Value ~ Expectations, family = binomial(link = logit), data = ev.clean)
> summary(ev.fit)

Call:
glm(formula = Value ~ Expectations, family = binomial(link = logit),
    data = ev.clean)

Deviance Residuals:
    Min       1Q   Median       3Q      Max
-2.4374   0.3245   0.3245   0.3245   1.6120

Coefficients:
             Estimate Std. Error z value Pr(>|z|)
(Intercept)   -0.9808     0.6770  -1.449    0.147
Expectations   3.8986     0.9926   3.928 8.58e-05 ***
---
Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1

(Dispersion parameter for binomial family taken to be 1)

    Null deviance: 50.040  on 49  degrees of freedom
Residual deviance: 28.668  on 48  degrees of freedom
AIC: 32.668

Number of Fisher Scoring iterations: 5

> curve(expr = exp(ev.fit$coefficients[1] + ev.fit$coefficients[2] * x) /
+  (1 + exp(ev.fit$coefficients[1] + ev.fit$coefficients[2] * x)),
+  col = 'firebrick', main = expression(logit(pi) == -0.9808 + 3.8986*x),
+  ylab = expression(pi), xlab = expression(x[1]),
+  ylim = c(0,1))
> exp(ev.fit$coefficients[2])
Expectations
    49.33333
>
> ev.pred0 <- ev.fit$coefficients[1] + (ev.fit$coefficients[2] * 0)    # lower logit link
> ev.pred1 <- ev.fit$coefficients[1] + (ev.fit$coefficients[2] * 1)    # upper logit link
> as.numeric(exp(ev.pred0)/(1 + exp(ev.pred0)))                                 # 0.27
[1] 0.2727273
> as.numeric(exp(ev.pred1)/(1 + exp(ev.pred1)))                                 # 0.94
[1] 0.9487179
>
> ev.graph <- ev.clean[,c(3,4)]
> ev.graph[1] <- as.factor(ev.graph$Value)
> ev.graph[2] <- as.factor(ev.graph$Expectations)
> ev.graph <- ifelse(ev.graph == 1, 'Yes', 'No')
> ev.graph <- as.data.frame(ev.graph)
>
> ggplot(ev.graph, aes(x = Value, fill = Expectations)) + geom_bar() +
+ labs(title = 'Expectation Communication and Feelings of Value') +
```

```
+ scale_fill_manual(values = c('firebrick', 'navy'))+
+ westcarts_theme
```