Hospital Supplier Analysis

Executive Summary:

Using a combination of contingency table investigation, GLM Net Modelling Techniques and general GLM, I have estimated that for the Purchase Order Data set given, which chronicled results during a 36 Month Period, that in the 37th Month, the proportion of Purchase Orders that will be owned by Credobased suppliers and by Small-Business based suppliers (for the CLPS – R&D Area within Johnson & Johnson) will be 0.069707 and 0.1629539 respectively.

Introduction:

We are given Purchase Order Data from Johnson & Johnson, specifically taken from the R&D Area, which is also called CLPS. This data has 907,408 observations consisting of 29 variables. Our variables of interest are 2 of these 29 variables:

- 1. Credo.Spend.Ind: This is a binary variable that acts as an indicator of whether or not the supplier of one of the observations is determined to be diverse (which essentially means that the business is woman or minority owned) by ARIBA standards. It takes two values: "Y", which indicates that the supplier is considered diverse and "N", which indicates that the supplier is not considered diverse. We are interested in those observations that take the value "Y". We will refer to observations that take the value "Y" as Credo observations.
- 2. Business.Size.Code: This is a categorical variable that refers to the size of the supplier's business, as classified by the government. It takes 4 values: "0", "D", "L" and "S" where the latter two represent large and small businesses. We are interested in those observations that take the value "S". We will refer to observations that take the value "S" as Small Business (or SB) observations.

The data gives Purchase Order information over a 36-month period from 1/2010 to 12/2012, which we will call Months 1 to 36 for convenience. The purpose of this month is to use the data given to estimate the proportion of total observations that are Credo observations and the proportion of total observations that are Small Business observations in the 37th month (which would be 1/2013).

The general analysis plan for this project involves the following steps, which will be expanded upon in the results section:

- 1. Extract the individual dates for each observation in the Purchase Order Data and set it equal to a number between 1 and 36
- 2. Perform proper investigative techniques within the Purchase Order Data to find several levels of categories which are associated with high proportions of SB and Credo
- 3. Create covariates for each observation based on the results of Step 2.
- 4. Create two covariate matrices (one for Credo, one for SB), which will have two components: the covariates chosen in Step 3 and time series components, which will be Credo or SB values during a given month.
- 5. Using the two covariate matrices, create two smaller matrices which each have 33 months, where each observation has the average value for each covariate for each month, as well as the proportion of the response (SB or Credo) for the last three months.
- 6. Using the matrices from Step 5, use appropriate GLM Models to estimate the proportion of Credo and SB for the 37th month.

RESULTS

Creation of Time Series Component:

First, I read the PO Data file into R using read.csv. Then, I decided to create an additional variable called poMonth which would indicate which month (out of 36) that each of the observations belonged to. I did this by extracting the month and year from the variable PO.Create.Date using the strsplit function and the ldply function within the plyr package. Then using the year and month, I filled out poMonth to index each observation as belonging to one of the months between 1 and 36.

Next, to get a general idea of what each proportion looked like through the 36 months, I created contingency tables for Month and Credo and Month and Small Business and then plotted each of them by month, also plotting their overall overages (Figures 1 and 2). Additionally, the tables containing these values are Figures 3 and 4.

Figure 1 shows that Credo Percentage for the most part shows a random pattern, although we do note that around the 30th Month there appears to be a relative drop-off where an increase only occurs at the very last month. Additionally, the overall average for Credo Percentage for these 36 months is 0.1006592, though majority of points are somewhat higher or lower than the average.

Figure 2 shows that Small Business Percentage also has a series of ups and downs in a random fashion but unlike Credo Percentages, the variance exhibited by the Small Business Proportion appears to be a bit smaller. Also, the overall average for Small Business percentage is .1919467.

Keeping this information in mind, I decided that to predict both proportions for the 37th month, I would create a GLM Model, that would incorporate time series terms (proportions in previous months) as well as covariates that I would manually extract from the data.

Methodology for Creating New Covariates:

On top of the time series terms, which would be proportion of Credo or Small Business for a particular month, I also wanted to add various other covariates extracted from the Purchase Order Data. I did this with a systematic approach of studying proportion trends for many subgroups.

To find subgroups, I took one of the 29 variables and created a contingency table between that variable and the variable of interest (Credo or Small Business). Then, using that table for each level of the variable, I found the count of the number of observations that had that level value and also had the value of the variable of interest. Then, I divided this number by the total number of observations that had that level value to find the proportion of Purchase Orders with the variable of interest. I tabulated this number for each level of the variable and subtracted the overall percentage value from this value. I took the absolute value of this and sorted the observations from highest absolute difference to lowest. If there were a large number of levels, I filtered this table to only show observations with high absolute differences and high total occurrence. Using this sorted table, if one of the levels of a variable exhibited a high deviation from the overall percentage of the variable of interest, I would use it as the basis of a new covariate, which would be a binary variable with value 1 if an observation exhibited that level of that variable and equal to 0 otherwise.

I exhibit this methodology by showing as an example, the process by which I extracted covariates for my Credo models based on values of Company. Looking just at Credo Proportion, I attempt to create new covariates for my GLM Model based on the levels of the variable Company. Company has 13 different levels and using the table command I created a contingency table that calculated the proportion of Credo observations within each of the 13 levels. Additionally, I also calculated the difference between each of these proportions and the overall Credo proportion for the entire dataset, 0.1006592. I found the absolute value of this difference and sorted the table by this value. This table is shown in Figure 5. As we can see, the Company levels HCS, Nutritionals and PR all deviate from average Credo percentage by 10% or more, with Credo proportion values of 0.307004713, 0.262573964 and 0.212037037 respectively. As such, I use this as a basis to create the following 3 variables:

$$1. X_1 = \begin{cases} 1 & \text{if } Company = HCS \\ 0 & \text{otherwise} \end{cases}$$

$$2. X_2 = \begin{cases} 1 & \text{if } Company = Nutritionals} \\ 0 & \text{otherwise} \end{cases}$$

$$3. X_3 = \begin{cases} 1 & \text{if } Company = PR \\ 0 & \text{otherwise} \end{cases}$$

I continue this process for various other variables for both Credo and Small Business Proportions.

Summary of New Variables Created:

Credo:

I created contingency tables for Credo Proportion and the variables Company, Category.Name, Subcategory.Name, Business.Size.Code and JNJ.Site.Code in order to find covariates to add to my GLM model for Credo Proportion. The Company table can be seen in Figure 5, the Category Name table can be seen in Figure 6, a subset of the Subcategory Name table can be seen in Figure 7, the Business Size Code table can be seen in Figure 8 and a subset of the JNJ Site Code Table can be seen in Figure 9. Based on these tables, 13 Covariates were created. Each Covariate takes the form $X_i = \frac{1}{2} \sum_{i=1}^{n} \frac{1$

- $1\ if\ condition\ fulfilled$. The 13 conditions for the covariates are listed below: $0\ otherwise$
- 1. Company = HCS
- 2. Company = Nutritionals
- 3. Company = PR
- 4. Category.Name = Consulting- Labor and Professional Services
- 5. Subcategory.Name = Managed Service Provider
- 6. Subcategory.Name = Professional Services
- 7. Subcategory. Name = Temporary Staffing
- 8. Business.Size.Code = D
- 9. Business.Size.Code = S

- 10. JNJ.Site.Code = 171013
- 11. JNJ.Site.Code = 141018
- 12. JNJ.Site.Code = 198001
- 13. JNJ.Site.Code = 165999

Small Business:

I also created contingency tables for Small Business Proportion and the variables Company (Figure 10), Category.Name (which will be omitted since no significant deviations were found), Subcategory.Name (Figure 11), Credo.Spend.Ind (Figure 12) and JNJ.Site.Code (Figure 13) in order to find covariates to add to my GLM model for Small Business Proportion. The Company table can be seen in Figure 5, the Category Name table can be seen in Figure 6, a subset of the Subcategory Name table can be seen in Figure 7, the Business Size Code table can be seen in Figure 8 and a subset of the JNJ Site Code Table can be seen in Figure 9. Based on these tables, 12 Covariates were initially created and 7 more were added later. These covariates take the same form as the Credo covariates and their conditions for a response value of 1 are:

- 1. Company = PR
- 2. Company = J&J Medical
- 3. Company = Global Ortropaedics
- 4. Subcategory.Name = Clinical Data Management Technology
- 5. Subcategory.Name = Clinical R&D Medical Testing (non-lab)
- 6. Subcategory.Name = Product Development Engineering & Testing
- 7. Subcategory.Name = Professional Services
- 8. Subcategory.Name = Training and Development
- 9. Subcategory.Name = R&D Lab Supplies Equipment and Instrumentation
- 10. Subcategory. Name = Product Development Product Design & Prototyping
- 11. Subcategory.Name = Consulting
- 12. Subcategory.Name = Clinical Clinical Lab Services
- 13. Subcategory.Name = Memberships & Subscriptions
- 14. Credo.Spend.Ind = Y
- 15. JNJ.Site.Code = 165999
- 16. JNJ.Site.Code = 129001
- 17. JNJ.Site.Code = 620301
- 18. JNJ.Site.Code = 445501

Regression Models Chosen:

Credo:

Using the 13 variables, I created a matrix that consisted of the 907,408 observations, with 15 columns, one column referring to the indexed month, one column referring to the Credo binary value for that observation and the next 13 columns referring to the 13 covariates that we had defined. Next, I created a new matrix with 33 rows and 18 columns. Each of the rows refers to a single month (out of months 34-36), with the next column referring to the Credo Proportion for that month, the next 13 columns referring to the average of each of the covariates for that particular month and the last three columns referring to the Credo Proportions for the prior three months (which is the reason that we start the matrix at the 4th month). For each model, the y response is the Credo Proportion for the current month, while the 13 covariates and the 3 prior Credo proportion terms are where the explanatory terms are chosen from.

I initially fit a GLM Model (specifying family as Gaussian) for the full model using the entirety of the X matrix. Then, using the predict function, I predicted the Credo Proportion of the 37th month, which turned out to be 0.03783186. Then, I plotted the predicted fit using the full model, the actual proportions as well as the predicted value of the 37th month, which can be seen in Figure 14. Additionally, we do the exact same thing, but fitting the GLM Gaussian Model for a reduced model which only includes the 3 time series terms as covariates. This time, we get a predicted Credo Proportion of 0.07285621 and plot the predicted fit (Figure 15). Next, we wish to find the proper subset of covariates to model in a GLM. To do this, we make use of GLM Net, where the cv.glmnet function gives us the appropriate covariates among our full set of covariates to model in a GLM Model. Below, I show the list of covariates chosen by GLM Net:

```
> coef(cvfit, s = "lambda.min")
17 x 1 sparse Matrix of class "dqCMatrix"
(Intercept) 0.05862258
V1
V2
٧3
V4
٧5
            -0.03444804
٧7
             0.15996946
V8
ν9
V10
V11
V12
V13
V14
V15
             0.05176430
V16
```

Based on this, the 6th Covariate, 7th Covariate and the 2nd Time Series Covariate are considered appropriate to include in a GLM Model. I decided to use the 6th and 7th Covariates as well as all of the Time Series Covariates (since it would be odd to include one over the other in this instance) in a GLM Model. The results of this are listed below:

```
> sumfit
call:
glm(formula = y ~ newx, family = gaussian())
Deviance Residuals:
                         Median
                  10
                                         30
                                                   Max
-0.069707
                      -0.000319
                                   0.008471
          -0.008214
                                              0.031203
Coefficients:
            Estimate Std. Error t value Pr(>|t|)
(Intercept) 0.04497
                        0.02272
                                  1.980
                                          0.05765
newx1
            -1.31815
                        1.00836
                                 -1.307
                                          0.20177
                                          0.00454 **
newx2
             0.32406
                        0.10502
                                   3.086
newx3
            -0.52592
                        0.37025
                                  -1.420
                                          0.16652
newx4
             0.18613
                        0.25445
                                  0.732
                                          0.47054
             0.26283
                        0.22848
                                   1.150
                                         0.25973
newx5
Signif. codes: 0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
```

The predicted Credo Proportion for Month 37 given by this model is 0.069707. Additionally, the actual Credo Proportion Values, predicted Credo Proportion Values and predicted Credo Proportion for the 37th Mont hare plotted and shown in Figure 16. From this graph, we conclude that within the 4-36 Month period, the model appears to predict the value of Credo Proportion somewhat accurately and as a result, we will accept the estimated Credo Proportion Value of 0.069707 as a valid estimate.

Small Business:

Initially, I used 12 covariates as predictors for Small Business, but I wanted to get a more accurate result so I added 7 additional covariates. This ultimately did not make much of an improvement on my fitted model, but decided to keep them since the GLM Net gave the same result anyway.

So, using the 19 covariates, I created a matrix with all of the observations and 21 columns, done in the same way that I did for the Credo variables. Then I created the matrix with data from Months 4-33, where the first column referred to the month, the second column referred to the Small Business Proportion for that month, the next 19 columns referred to the average of the covariates for each of the months, and the last three columns referred to the average Small Business Proportion values for the prior 3 months.

I initially fit a GLM Model (specifying family as Gaussian) for the full model using the entirety of the X matrix. Then, using the predict function, I predicted the Small Business Proportion of the 37th month, which turned out to be 0.09155772. Then, I plotted the predicted fit using the full model, the actual proportions as well as the predicted value of the 37th month, which can be seen in Figure 17. Additionally, we do the exact same thing, but fitting the GLM Gaussian Model for a reduced model which only includes the 3 time series terms as covariates. This time, we get a predicted Small Business

Proportion of 0.1761756 and plot the predicted fit (Figure 18). Next, we wish to find the proper subset of covariates to model in a GLM. To do this, we make use of GLM Net, where the cv.glmnet function gives us the appropriate covariates among our full set of covariates to model in a GLM Model. Below, I show the list of covariates chosen by GLM Net:

```
> coef(cvfit, s = "lambda.min")
23 x 1 sparse Matrix of class "dgCMatrix"
(Intercept) 0.1769208
            1.6307093
٧1
V2
V3
V4
٧5
٧6
٧7
V8
ν9
V10
V11
V12
V13
V14
V15
V16
V17
V18
V19
V20
V21
V22
```

We note that only the first Covariate is significant. Additionally, when I ran this model with only 12 extra covariates instead of 19, I still got this same result from GLM Net. As a result, I decided to fit my GLM Model as the first Covariate and then the three time series terms. The results of this GLM Model are given below:

```
> sumfit
glm(formula = y \sim newx, family = gaussian())
Deviance Residuals:
      Min
                  1Q
                         Median
                                         3Q
                                                   Max
-0.162954 -0.004324
                       0.005424
                                   0.014409
                                              0.034172
Coefficients:
            Estimate Std. Error t value Pr(>|t|)
                                          0.00646 **
(Intercept) 0.12816
                        0.04366
                                   2.935
newx1
             5.75812
                        3.49070
                                   1.650
                                          0.10982
newx2
             0.03266
                        4.27625
                                   0.008
                                          0.99396
newx3
             0.19404
                        0.34821
                                   0.557
                                          0.58164
             6.66414
                        6.59414
                                   1.011 0.32056
newx4
```

Signif. codes: 0 '***' 0.001 '**' 0.05 '.' 0.1 ' ' 1

The predicted Small Business Proportion for Month 37 given by this model is 0.1629539. Additionally, the actual Small Business Proportion Values, predicted Small Business Proportion Values and predicted Small Business Proportion for the 37th Month are plotted and shown in Figure 19. From this graph, we conclude that within the 4-36 Month period, the model appears to predict the value of Credo Proportion somewhat accurately and as a result, we will accept the estimated Credo Proportion Value of 0.1629539 as a valid estimate.

Conclusion:

The purpose of this project was to use Purchase Order data during a 36 month period to try to estimate the proportion of Purchase Orders (for the CLPS- R&D area of Johnson & Johnson) in the 37th Month that are filled out by Credo-based suppliers or Small Business-based suppliers. I approached this problem by separating the large dataset by month and predicting each of the two proportions for each of the months by using a GLM model that uses a combination of time series variables and other covariates that are chosen based on subgroups. The time series variable for each month are the proportions for Credo or Small Business for each of the previous three months and the additional covariates were found as indicator variables for subgroups that were discovered by investigating relationships in contingency tables within the data. After using GLM Net to select which models to fit for both Responses, I have estimated that the proportion of Purchase Orders that will be filled by Credo and Small Business owned suppliers will be 0.069707 and 0.1629539 respectively.

Appendix:

Credo Percentage by Month 5 0 0 5 10 15 20 25 30 35

Month (1-36) *Figure 1*

> print(credo_table)

Total Credo Percentage

	N	Y	month_credo_splits	credo_above_average
1	28641		0.08457187	0
2	22395	2197	0.08933800	0
3	25530	2378	0.08520854	0
4	22518	2213	0.08948284	0
5	21249	2342	0.09927515	0
6	22470		0.09179095	0
7	19195		0.08302680	0
8	20524		0.07947614	0
9	19569		0.08324745	0
	20601		0.09992136	0
	27055		0.10903642	1
		3369	0.11903752	1
	35346		0.14306495	1
	24819		0.10719810	1
	27604		0.11366555	1
	22368		0.11909263	1
	21797		0.12250403	1
	22566		0.09282412	0
	18373		0.09945103	0
	20940		0.09362420	0
	19476		0.09489730	0
	19651		0.09692096	0
	26527		0.10330257	1
	30808		0.15673072	1
	39438		0.12098248	1
	29286		0.09655726	0
	28975		0.08969526	0
	22910		0.10029846	0
	22986		0.10431360	1
	20530		0.08348214	0
	16662		0.07211672	0
	17117		0.07968170	0
	14216		0.06932897	0
	14509	996	0.06423734	0
	13313	741	0.05272520	0
36	11172	1029	0.08433735	0

Figure 3

> print(sorted_credo_company_splits)							
		0.043798631	-0.0568606095				
			-0.0006630846				
credo_0							
	0.0	0006630846					
	N 4264 997 2553 4028 31589 44562 259667 98717 90254 81339 46706 117059	N Y 4264 1889 997 355 2553 687 4028 8 31589 6183 44562 8409 9972 515967 11894 98717 17332 90254 1598 81339 7333 34334 3109 17059 13006 credo_compar.	N Y credo_company_splits 4264 1889 0.307004713 997 355 0.262573964 2553 687 0.212037037 4028 8 0.001982161 31589 6183 0.163692682 44562 8409 0.158747239 259667 11894 0.04379861 98717 17332 0.149350705 90254 15198 0.14412244 8133 7333 0.082698033 34324 3109 0.082698033 34324 3109 0.083032877 46706 5936 0.112761673 117059 13006 0.099996156 credo_company_abs_diff 0.2063454728 0.1619147241 0.1113777967 0.0966770798 0.0630334420 0.05808590857 0.05808606095 0.0486914649 0.0434632039 0.0179612072 0.0176263637 0.0121024228				

Figure 5

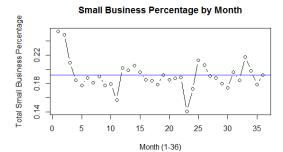


Figure 2

> print(sb_table)

	0	D	L	5	month_sb_splits	sb_above_average
1	0		23212		0.2535238	1
2	1		18415		0.2491461	1
3	0	87	21974	5847	0.2095098	1
4	0	128	20034	4569	0.1847479	0
5	0	380	19020	4191	0.1776525	0
6			19964		0.1883513	0
7	0		16999		0.1815793	0
8	3		18009		0.1901686	0
9	17		17477		0.1776445	0
10	3		18638		0.1793516	0
11			25287		0.1572482	0
12			22306		0.2019645	1
13	2		32608		0.1987296	1
14	4		21769		0.2057268	1
15	1		24602		0.1961534	1
16	0		20438		0.1853340	0
17	7		19891		0.1840177	0
18			20267		0.1790955	0
19			16172		0.1925301	1
20			18605		0.1853006	0
21			17349		0.1875174	0
22			17546		0.1886029	0
23			25247		0.1410607	0
24			30101		0.1726611	0
25	0		34772		0.2128783	1
26	0		25680		0.2060402	1
27	0		25621		0.1910148	0
28			20449		0.1880302	0
29			20869		0.1799088	0
30			18369		0.1741071	0
31			14332		0.1962466	1
32	2		14975		0.1850637	0
33	0		11868		0.2177414	1
34			12296		0.1980006	1
35			11400		0.1788103	0
36	1	189	9668	2343	0.1920334	1

Figure 4

> print(categ_credo_table)

	N Y categ_credo_splits
Consulting- Labor and Professional Services	264139 69723 0.20883778
Research & Development (Products & Packaging)	551930 21616 0.03768835
	categ_credo_diff
Consulting- Labor and Professional Services	0.10817854
Research & Development (Products & Packaging)	-0.06297089

Figure 6

> head(sorted_subcateg_credo_table)

> nead(sorted_subcated_cr	edo_ta	oie)					
				N	Y	subcateg_cr	edo_splits
Preclinical - Anatomical	Matls (& Testing	(Human)	21	12		0.3636364
Managed Service Provider				2442	1264		0.3410685
Professional Services				2625	1194		0.3126473
Temporary Staffing				140450	46203		0.2475342
Consulting				47542	15551		0.2464774
Benefits (Employees)				544	0		0.0000000
				subcat	eg_cre	do_diff	
Preclinical - Anatomical	Matls (& Testing	(Human)		0.7	2629771	
Managed Service Provider						2404093	
Professional Services						2119880	
Temporary Staffing						1468750	
Consulting						1458182	
Benefits (Employees)						1006592	
				subcat	eg_cre	do_absdiff	
Preclinical - Anatomical	Matls	& Testing	(Human)			0.2629771	
Managed Service Provider						0.2404093	
Professional Services						0.2119880	
Temporary Staffing						0.1468750	
Consulting						0.1458182	
Benefits (Employees)						0.1006592	

> print(sorted_bus_credo_table)

	N	Y	bus_credo_splits	bus_credo_diff	bus_credo_absdiff
D	5	6937	0.99927975	0.89862051	0.89862051
5	128856	45318	0.26018809	0.15952885	0.15952885
0	63	0	0.00000000	-0.10065924	0.10065924
L	687145	39084	0.05381774	-0.04684151	0.04684151

Figure 8

Figure 7

S	head	Sorted	site	credo	tabl	6)

<pre>> head(sorted_site_credo_table)</pre>									
N Y	site_credo_splits	site_credo_diff	site_credo_absdiff	large_group					
171013 762 1051	0.5797022	0.4790429	0.4790429	1					
141018 2563 1415	0.3557064	0.2550471	0.2550471	1					
198001 748 386	0.3403880	0.2397288	0.2397288	1					
165999 1527 745	0.3279049	0.2272457	0.2272457	1					
198011 956 416	0.3032070	0.2025478	0.2025478	1					
138239 3036 1276	0.2959184	0.1952591	0.1952591	1					

Figure 9

> sorted_subcateg_sb_table[1:10,]

> sorted_subcateg_sb_table[1.10,]					
	0	D	L	5	
Clinical - Data Management Technology	0	0	207	942	
Clinical - R&D Medical Testing (non-lab)	0	0	394	1766	
Product Development - Engineering & Testing	0	0	472	942	
Professional Services	ō	ō	1746	2073	
Training and Development	2			11342	
R&D Lab Supplies - Equipment and Instrumentation			73800		
Product Development - Product Design & Prototyping				689	
Consulting	18		34862		
Clinical - Clinical Lab Services	10		4601		
	0				
Memberships & Subscriptions			2438		
	su	bcate			subcateg_sb_diff
Clinical - Data Management Technology				98433	0.6278966
Clinical - R&D Medical Testing (non-lab)				75926	
Product Development - Engineering & Testing				51952	
Professional Services			0.542	28123	0.3508655
Training and Development				38417	
R&D Lab Supplies - Equipment and Instrumentation			0.470	08566	0.2789099
Product Development - Product Design & Prototyping			0.45	31117	0.2661650
Consulting			0.446	55630	0.2546163
Clinical - Clinical Lab Services			0.444	19940	0.2530472
Memberships & Subscriptions			0.439	90244	0.2470777
	sul	bcated	ı sb al	osdiff	large_group
Clinical - Data Management Technology				278966	
Clinical - R&D Medical Testing (non-lab)				256459	
Product Development - Engineering & Testing				742485	
Professional Services				508655	
Training and Development				118949	
R&D Lab Supplies - Equipment and Instrumentation				789099	
Product Development - Product Design & Prototyping				561650	
Consulting				546163	
Clinical - Clinical Lab Services				530472	
Memberships & Subscriptions			0.24	170777	1

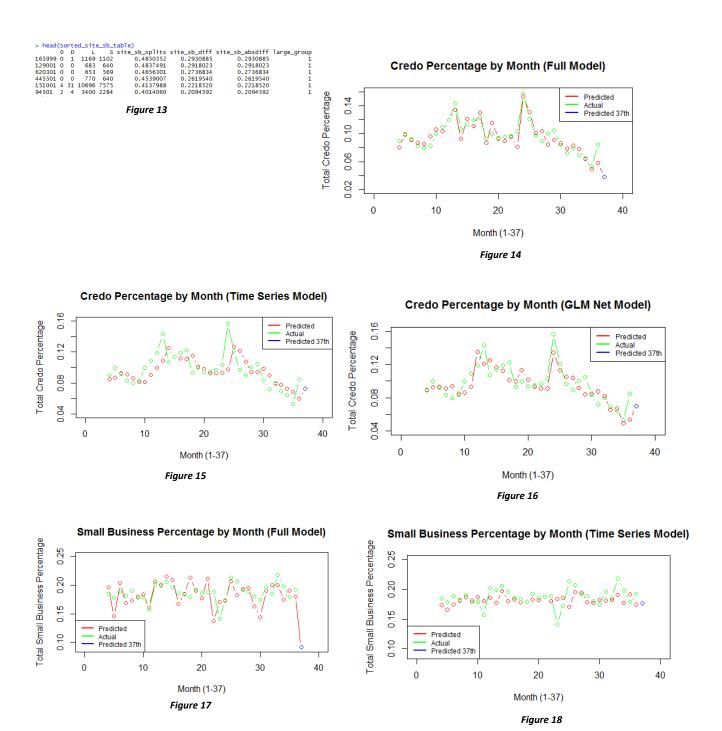
Figure 11

PR J&J Medical Global Ortropaedics Global Surgery Pharm Commercial Nutritionals JSC OTC Global Medical Solution Pharm R&D Consumer Products HCS 0.052875/53 0.049928958 0.044207033 0.017364792 0.014200295 0.010243536 0.009683712 0.006996301

Figure 10

>	> print(sorted_credo_sb_table)									
	0	D	L	5	credo_sb_splits	credo_sb_diff	credo_sb_absdiff			
Υ	0	6937	39084	45318	0.4961517	0.30420497	0.30420497			
N	63	5	687145	128856	0.1578984	-0.03404832	0.03404832			

Figure 12



Small Business Percentage by Month (GLM Net Model)

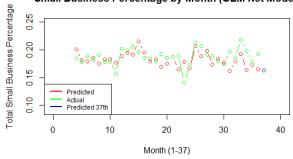


Figure 19