Sports Drinks Analysis

SCM 651 – Project Report

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Introduction:

This project explores Dominick's store-level database, which was obtained during a span of seven years – 1989 to 1997. We have chosen to perform analysis on the product category – Sports Drinks.

Data Selection:

To perform this analysis, we selected a subset consisting of three brands of sports drinks. To obtain a better understanding of various brands of sports drinks trends, we decided to choose two premium brands and one low price brand as our subset for data analysis.

We used the file: 'Sports drinks high movement UPC' to help us finalize on the three brands.
Chosen premium brands: All Sport Lemon Lime and All Sport Cherry Slam
Chosen low priced brand: Powerade Tidal Burst

UPC	BRAND	SIZE	CASE
1200000315	ALLSPORT CHERRY SLAM	32 OZ	12
1200000735	ALL SPORT LEMON LIME	32 OZ	12
1200000757	ALL SPORT FRUIT PUNC	32 OZ	12
5200003805	GATORADE FRUIT PUNCH	32 OZ	12
5200003925	GATORADE LEMON/LIME	32 OZ	12
5200003940	GATORADE ORANGE DRIN	32 OZ	12
5200032810	GATORADE SPRTS BTL	20 OZ	24
5200032814	GATORADE SPTS BTL F	20 OZ	24
5200032841	GTRADE SPTS BTL CL	20 OZ	24
5200032842	GATORADE SPSTS BTL	20 OZ	24
5200032873	GATORADE WATERMELON-	32 OZ	12
5200033820	GATORADE COOL BLUE R	32 OZ	12
5200033830	GATORADE FRUIT PUNCH	64 OZ	8
5200033831	GATORADE ORANGE	64 OZ	8
5200033832	GATORADE LEMON LIME	64 OZ	8
5200033833	GATORADE LEMONADE	64 OZ	8
5200033934	GATORADE LEMON ICE	32 OZ	12
4900001923	POWERADE FRUIT PUNCH	32 OZ	12
4900002314	POWERADE MOUNTAIN BL	32 OZ	12
4900002450	POWERADE TIDAL BURST	32 OZ	12

Data Preparation:

- To create our subset file, we established relationships between three data sets 'Weekly movement data', 'UPC and product description' and 'Store demographics'. These data sets were provided as a part of Dominick's database of Sports Drinks.

- We then used Access to combine information from these three datasets for the selected brand of sports drinks, and created a new subset.

- We decided to create a new factor named “SEASON” in our subset. To do this, we considered the factor ‘REM’, and provided the below condition in Access to form seasons:

  SEASON: IIF([REM]>10 And [REM]<24, “WINTER”, IIF([REM]>23 And [REM]<37, “SPRING”, IIF([REM]>36 And [REM]<50, “SUMMER”, “FALL”)))

A snippet of the newly created subset, with the selected 3 brands of Sports Drinks.

new subset

UPC	BRAND	SIZE	CASE	STOREWEEK	STORE	WEEK	REM	SEASON	MOVE	logmove	QTY	PRICE	logprice
1200000315	ALLSPORT CHERRY SLAM	32 OZ	12	2363	2	363	51	FALL	5	1.6094379124341	1	1.31	0.27002713721
1200000315	ALLSPORT CHERRY SLAM	32 OZ	12	2364	2	364	0	FALL	3	1.09861228866811	1	0.99	-1.00503358535015E
1200000315	ALLSPORT CHERRY SLAM	32 OZ	12	2365	2	365	1	FALL	8	2.07944154167984	1	0.89	-0.116533816255
1200000315	ALLSPORT CHERRY SLAM	32 OZ	12	2366	2	366	2	FALL	6	1.79175946922805	1	0.89	-0.116533816255
1200000315	ALLSPORT CHERRY SLAM	32 OZ	12	2367	2	367	3	FALL	6	1.79175946922805	1	0.89	-0.116533816255
1200000315	ALLSPORT CHERRY SLAM	32 OZ	12	2368	2	368	4	FALL	6	1.79175946922805	1	0.89	-0.116533816255
1200000315	ALLSPORT CHERRY SLAM	32 OZ	12	2372	2	372	8	FALL	2	0.693147180559945	1	1.39	0.3293037471
1200000315	ALLSPORT CHERRY SLAM	32 OZ	12	5352	5	352	40	SUMMER	1	0	1	0.99	-1.00503358535015E
1200000315	ALLSPORT CHERRY SLAM	32 OZ	12	8352	8	352	40	SUMMER	6	1.79175946922805	1	0.99	-1.00503358535015E
1200000315	ALLSPORT CHERRY SLAM	32 OZ	12	8353	8	353	41	SUMMER	4	1.38629436111989	1	1.01	9.95033085316809E
1200000315	ALLSPORT CHERRY SLAM	32 OZ	12	8354	8	354	42	SUMMER	2	0.693147180559945	1	0.99	-1.00503358535015E
1200000315	ALLSPORT CHERRY SLAM	32 OZ	12	8355	8	355	43	SUMMER	12	2.484906649788	1	0.99	-1.00503358535015E
1200000315	ALLSPORT CHERRY SLAM	32 OZ	12	8362	8	362	50	FALL	47	3.85014760171006	1	0.99	-1.00503358535015E
1200000315	ALLSPORT CHERRY SLAM	32 OZ	12	8363	8	363	51	FALL	8	2.07944154167984	1	1.05	0.048790164169
1200000315	ALLSPORT CHERRY SLAM	32 OZ	12	8364	8	364	0	FALL	6	1.79175946922805	1	0.99	-1.00503358535015E
1200000315	ALLSPORT CHERRY SLAM	32 OZ	12	8365	8	365	1	FALL	12	2.484906649788	1	0.89	-0.116533816255
1200000315	ALLSPORT CHERRY SLAM	32 OZ	12	8366	8	366	2	FALL	15	2.70805020110221	1	0.89	-0.116533816255
1200000315	ALLSPORT CHERRY SLAM	32 OZ	12	8367	8	367	3	FALL	12	2.484906649788	1	0.89	-0.116533816255
1200000315	ALLSPORT CHERRY SLAM	32 OZ	12	8368	8	368	4	FALL	7	1.94591014905531	1	0.89	-0.116533816255
1200000315	ALLSPORT CHERRY SLAM	32 OZ	12	8369	8	369	5	FALL	3	1.09861228866811	1	1.09	8.61776962410524E
1200000315	ALLSPORT CHERRY SLAM	32 OZ	12	8370	8	370	6	FALL	3	1.09861228866811	1	1.09	8.61776962410524E
1200000315	ALLSPORT CHERRY SLAM	32 OZ	12	8371	8	371	7	FALL	1	0	1	1.09	8.61776962410524E
1200000315	ALLSPORT CHERRY SLAM	32 OZ	12	8373	8	373	9	FALL	12	2.484906649788	1	1.09	8.61776962410524E
1200000315	ALLSPORT CHERRY SLAM	32 OZ	12	9347	9	347	35	SPRING	1	0	1	1.29	0.254642218373
1200000315	ALLSPORT CHERRY SLAM	32 OZ	12	9352	9	352	40	SUMMER	1	0	1	0.99	-1.00503358535015E
1200000315	ALLSPORT CHERRY SLAM	32 OZ	12	9354	9	354	42	SUMMER	2	0.693147180559945	1	0.99	-1.00503358535015E
1200000315	ALLSPORT CHERRY SLAM	32 OZ	12	9357	9	357	45	SUMMER	2	0.693147180559945	1	1.29	0.254642218373
1200000315	ALLSPORT CHERRY SLAM	32 OZ	12	9359	9	359	47	SUMMER	1	0	1	0.99	-1.00503358535015E
1200000315	ALLSPORT CHERRY SLAM	32 OZ	12	9361	9	361	49	SUMMER	1	0	1	0.99	-1.00503358535015E
1200000315	ALLSPORT CHERRY SLAM	32 OZ	12	9363	9	363	51	FALL	2	0.693147180559945	1	1.14	0.131028262406
1200000315	ALLSPORT CHERRY SLAM	32 OZ	12	9365	9	365	1	FALL	4	1.38629436111989	1	0.89	-0.116533816255

Record: 1 of 8349 No Filter Search

Data Analysis:

We used different statistical tools like R and excel to answer a few data questions, which then provided us with a better insight on our subset.
Our research data questions, and the corresponding insights obtained on them are as follows:

- **How does the demand for a brand depend on price? What is the price elasticity of demand of a brand?**

To understand this, we created a linear model with ‘logmove’ i.e. the demand of a product, as the dependent variable and the remaining factors as independent variables.

```
Call:
lm(formula = logmove ~ AGE9 + AGE60 + BRAND + EDUC + ETHNIC +
    Feat + HHLARGE + HHSINGLE + HVAL150 + INCOME + logprice +
    NOCAR + NWHITE + POVERTY + REM + RETIRED + SEASON + SINGLE +
    STOREWEEK + UNEMP + WORKWOM + BRAND * logprice, data = SportsDrinks)
```

To better understand the effect of ‘logprice’ on ‘logmove’, with respect to each of the brands i.e., All Sport Lemon Lime, All Sport Cherry Slam and Powerade Tidal Burst, we haven taken an additional combinational variable – *BRAND * logprice.*

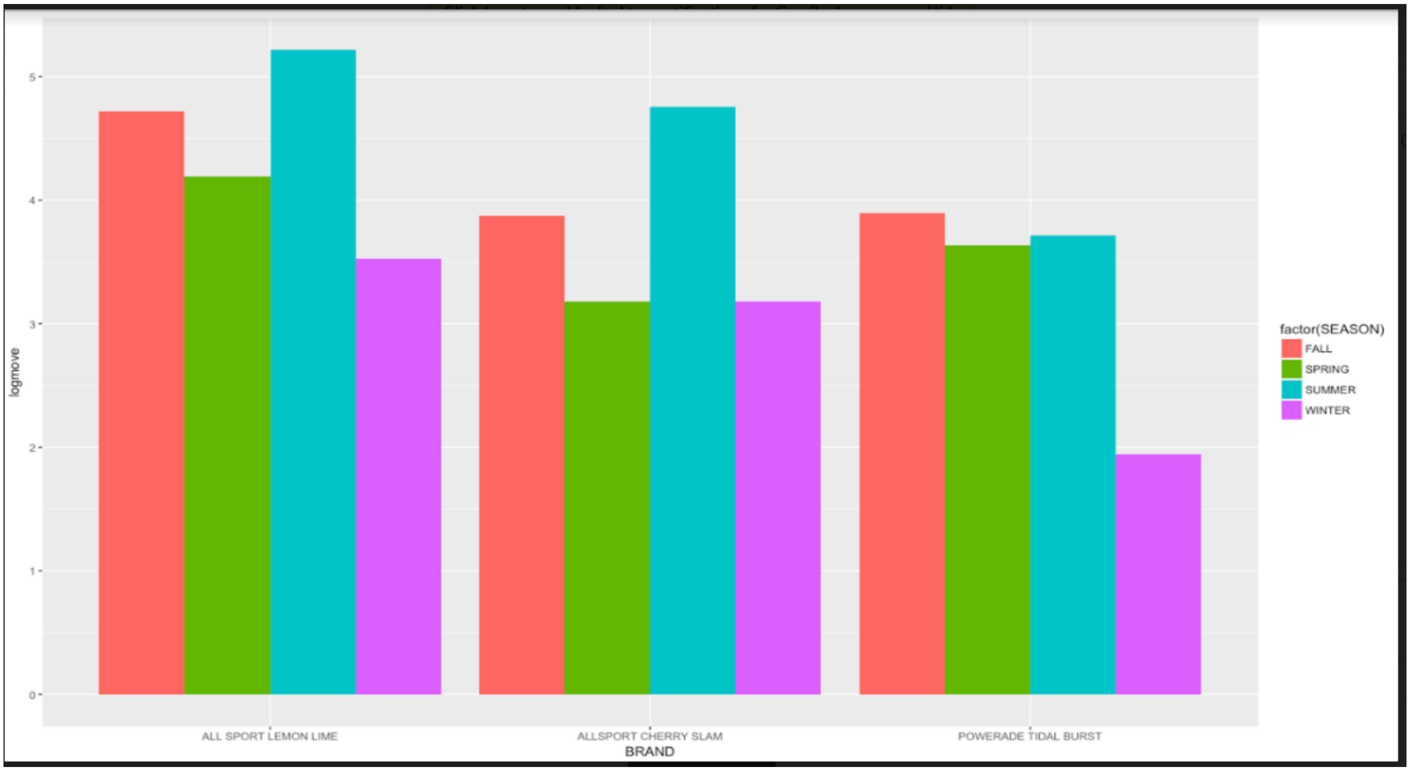
```
NWHITE                                  -3.0066939605  0.3602895106  -8.345  < 2e-16 ***
POVERTY                                  3.9490646447  1.4734660796   2.680 0.007374 **
REM                                      0.0112568075  0.0008212779  13.706  < 2e-16 ***
RETIRED                                 -4.2512678468  1.4722030047  -2.888 0.003891 **
SEASON[T.SPRING]                        -0.5485208377  0.0327033350 -16.773  < 2e-16 ***
SEASON[T.SUMMER]                        -0.1099196504  0.0327954755  -3.352 0.000807 ***
SEASON[T.WINTER]                        -0.3511093478  0.0329293977 -10.662  < 2e-16 ***
SINGLE                                   0.4970578117  0.8077827948   0.615 0.538350
STOREWEEK                                0.0000041258  0.0000003287  12.552  < 2e-16 ***
UNEMP                                   13.9747482465  2.2795945965   6.130 9.17e-10 ***
WORKWOM                                  5.4865128497  1.1983362673   4.578 4.75e-06 ***
BRAND[T.ALLSPORT CHERRY SLAM]:logprice  -0.2891685803  0.1810658952  -1.597 0.110296
BRAND[T.POWERADE TIDAL BURST]:logprice   0.1843604778  0.1963734749   0.939 0.347847
---
Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1

Residual standard error: 0.8172 on 8322 degrees of freedom
Multiple R-squared:  0.3158, Adjusted R-squared:  0.3136
F-statistic: 147.7 on 26 and 8322 DF,  p-value: < 2.2e-16
```

To calculate the price elasticity of each of the brands, we have considered the value of coefficient corresponding to the logprice of each of the brand.

Price elasticity of demand for ALL SPORT LEMON LIME: **-1.9679988575**
Price elasticity of demand for ALLSPORT CHERRY SLAM: -1.9679988575 - 0.2891685803 = **-1.6788**
Price elasticity of demand for POWERADE TIDAL BURST: -1.9679988575 + 0.1843604778 = **-1.7836**

Conclusion: Through this analysis we see that, the price elasticity of demand for the brand AllSport Cherry Slam is the highest and All Sport Lemon Lime is the lowest. Thus, we can state that for a small change in price of Cherry Slam, there is larger change in its demand. Hence, to increase the sales of Cherry Slam, we can reduce its price.

Below graph represents the demand for each brand of Sports Drinks, during each of the 4 seasons – Fall, Spring, Summer and Winter.



Here, we can clearly see that – when compared to the remaining two brands, the demand for Lemon Lime is the highest in all the seasons, as its price elasticity is the least.

➢ How does demand depend on whether the product is on sale (Feat =1)?

To understand this, we created a linear model with 'logmove' i.e. the demand of a product, as the dependent variable and the remaining factors as independent variables.

```
Call:
lm(formula = logmove ~ AGE9 + AGE60 + BRAND + EDUC + ETHNIC +
    Feat + HHLARGE + HHSINGLE + HVAL150 + INCOME + logprice +
    NOCAR + NWHITE + POVERTY + REM + RETIRED + SEASON + SINGLE +
    +STOREWEEK + UNEMP + WORKWOM + INCOME + logprice + NOCAR +
    NWHITE + POVERTY + REM + RETIRED + SEASON + SINGLE + STOREWEEK +
    UNEMP + WORKWOM + BRAND * Feat, data = SportsDrinks)
```

To better understand the effect of 'Feat' on 'logmove', with respect to each of the brands i.e., All Sport Lemon Lime, All Sport Cherry Slam and Powerade Tidal Burst, we haven taken an additional combinational variable – *BRAND * Feat.*

```
--
NOCAR                               1.3682202340   0.3686223366   3.712 0.000207 ***
NWHITE                             -2.9990492638   0.3601261975  -8.328  < 2e-16 ***
POVERTY                             3.9248749278   1.4727328892   2.665 0.007713 **
REM                                 0.0109374237   0.0008148545  13.423  < 2e-16 ***
RETIRED                            -4.2387109938   1.4713550006  -2.881 0.003977 **
SEASON[T.SPRING]                   -0.5454425570   0.0326981122 -16.681  < 2e-16 ***
SEASON[T.SUMMER]                   -0.1003607175   0.0326516708  -3.074 0.002121 **
SEASON[T.WINTER]                   -0.3645311652   0.0329544873 -11.062  < 2e-16 ***
SINGLE                              0.5251084984   0.8074069217   0.650 0.515475
STOREWEEK                           0.0000041328   0.0000003286  12.579  < 2e-16 ***
UNEMP                              13.9515194575   2.2781765170   6.124 9.54e-10 ***
WORKWOM                             5.4854284624   1.1975824063   4.580 4.71e-06 ***
BRAND[T.ALLSPORT CHERRY SLAM]:Feat  0.1803015677   0.0548826450   3.285 0.001023 **
BRAND[T.POWERADE TIDAL BURST]:Feat  0.0958139509   0.0488175723   1.963 0.049715 *
---
Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1

Residual standard error: 0.8168 on 8322 degrees of freedom
Multiple R-squared:  0.3164, Adjusted R-squared:  0.3143
F-statistic: 148.2 on 26 and 8322 DF,  p-value: < 2.2e-16
```

To calculate the effect of Sale of each of the brands, we have considered the value of coefficient corresponding to the Feat of each of the brand.

Dependency of demand on Feat for ALL SPORT LEMON LIME: **0.1809583378**
Dependency of demand on Feat for ALLSPORT CHERRY SLAM: 0.1803015677 + 0.1809583378 = **0.3618**
Dependency of demand on Feat for POWERADE TIDAL BURST: 0.0958139509 + 0.1809583378 = **0.2767**

Conclusion: Through this analysis we see that, there is a highest increase in demand of All Sport Cherry Slam during a Sale (Feat = 1), whereas there is a least increase in demand of All Sport Lemon Lime during a Sale (Feat = 1).

- ## What demographic factors affect demand?

To understand this, we first created a linear model with 'logmove' i.e. the demand of a product, as the dependent variable and the remaining factors as independent variables.

```
Call:
lm(formula = logmove ~ AGE9 + AGE60 + BRAND + EDUC + ETHNIC +
    Feat + HHLARGE + HHSINGLE + HVAL150 + INCOME + logprice +
    NOCAR + NWHITE + POVERTY + REM + RETIRED + SEASON + SINGLE +
    +STOREWEEK + UNEMP + WORKWOM + INCOME + logprice + NOCAR +
    NWHITE + POVERTY + REM + RETIRED + SEASON + SINGLE + STOREWEEK +
    UNEMP + WORKWOM + BRAND * Feat, data = SportsDrinks)
```

The demographic variables are considered significant at a 90% level of confidence, if their probability is less than 0.1.

```
Residuals:
     Min       1Q   Median       3Q      Max
-2.93640 -0.49447  0.07801  0.55833  2.48301

Coefficients:
                                         Estimate     Std. Error t value Pr(>|t|)
(Intercept)                           -14.9158079346   2.0455416517  -7.292 3.34e-13 ***
AGE9                                   -0.8631792598   1.9179176926  -0.450 0.652678
AGE60                                   7.8953699347   1.1531062360   6.847 8.07e-12 ***
BRAND[T.ALLSPORT CHERRY SLAM]          -0.6764352636   0.0439775197 -15.381  < 2e-16 ***
BRAND[T.POWERADE TIDAL BURST]          -0.5668792833   0.0386292598 -14.675  < 2e-16 ***
EDUC                                   -0.4116364741   0.2545482023  -1.617 0.105889
ETHNIC                                  1.5640288388   0.3704432085   4.222 2.45e-05 ***
Feat                                    0.1809583378   0.0289361456   6.254 4.21e-10 ***
HHLARGE                                 0.5758535352   1.1202837186   0.514 0.607248
HHSINGLE                               -1.2994989915   0.6431985469  -2.020 0.043377 *
HVAL150                                -0.0170106006   0.1160723589  -0.147 0.883489
INCOME                                  1.1081285530   0.1523858356   7.272 3.87e-13 ***
logprice                               -1.9279757805   0.1022335815 -18.859  < 2e-16 ***
NOCAR                                   1.3682202340   0.3686223366   3.712 0.000207 ***
NWHITE                                 -2.9990492638   0.3601261975  -8.328  < 2e-16 ***
POVERTY                                 3.9248749278   1.4727328892   2.665 0.007713 **
REM                                     0.0109374237   0.0008148545  13.423  < 2e-16 ***
RETIRED                                -4.2387109938   1.4713550006  -2.881 0.003977 **
SEASON[T.SPRING]                       -0.5454425570   0.0326981122 -16.681  < 2e-16 ***
SEASON[T.SUMMER]                       -0.1003607175   0.0326516708  -3.074 0.002121 **
SEASON[T.WINTER]                       -0.3645311652   0.0329544873 -11.062  < 2e-16 ***
SINGLE                                  0.5251084984   0.8074069217   0.650 0.515475
STOREWEEK                               0.0000041328   0.0000003286  12.579  < 2e-16 ***
UNEMP                                  13.9515194575   2.2781765170   6.124 9.54e-10 ***
WORKWOM                                 5.4854284624   1.1975824063   4.580 4.71e-06 ***
BRAND[T.ALLSPORT CHERRY SLAM]:Feat      0.1803015677   0.0548826450   3.285 0.001023 **
BRAND[T.POWERADE TIDAL BURST]:Feat      0.0958139509   0.0488175723   1.963 0.049715 *
```

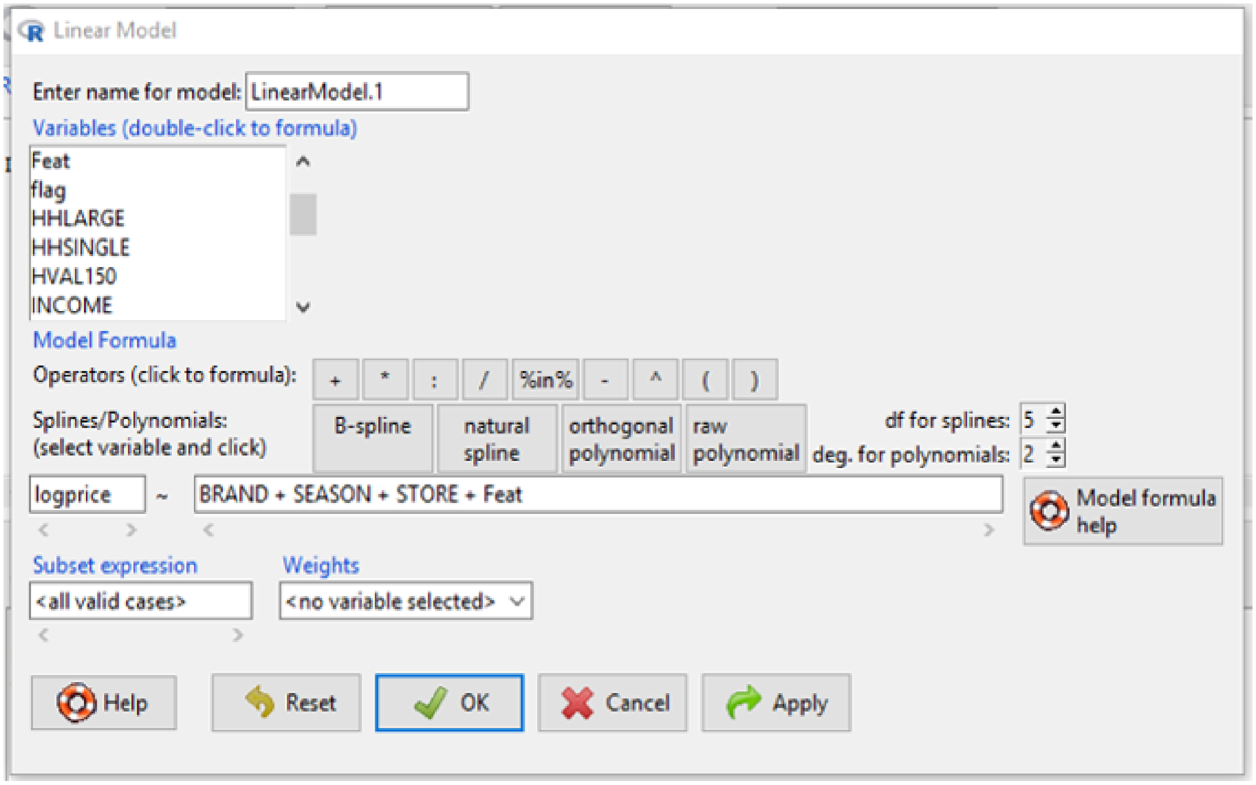
Conclusion: Through this analysis we see that, the following are the significant and non-significant demographic variables:

Significant demographic variables: Age 60, Ethnic, Income, NoCar, Nwhite, Retired, UnEmp, WorkWom, Poverty, HHSingle

Non - Significant demographic variables: Age 9, Educ, HHLarge, Hval150, Single

- **How does prices vary across brands?**

To solve this problem, we use the Rcmdr---Statistics---Fit Model---Linear Model.



We choose the [logprice] as dependent variable, and [BRAND], [SEASON], [STORE] and [Feat] as independent variables. And below is the outcome.

```
Call:
lm(formula = logprice ~ BRAND + SEASON + STORE + Feat, data = Dataset)

Residuals:
     Min       1Q   Median       3Q      Max
-0.34368 -0.06384  0.00203  0.07061  0.27880

Coefficients:
                               Estimate  Std. Error t value Pr(>|t|)
(Intercept)                  0.21616535  0.00329976  65.509  < 2e-16 ***
BRAND[T.ALLSPORT CHERRY SLAM] -0.04951889  0.00292890 -16.907  < 2e-16 ***
BRAND[T.POWERADE TIDAL BURST] -0.02377691  0.00274720  -8.655  < 2e-16 ***
SEASON[T.SPRING]             -0.00184857  0.00320456  -0.577   0.5641
SEASON[T.SUMMER]              0.00526253  0.00237259   2.218   0.0266 *
SEASON[T.WINTER]              0.02788266  0.00362552   7.691 1.63e-14 ***
STORE                         0.00015255  0.00002841   5.369 8.12e-08 ***
Feat                         -0.17572544  0.00219462 -80.071  < 2e-16 ***
---
Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
```

From the outcome, we can get the equations for each brand.

ALLSPORT LEMON LIME: *(ACS=0, PTB=0)*

Logprice

= **0.2162** -0.0018*SPRING + 0.0053*SUMMER + 0.0279*WINTER + 0.0002*STORE
– **0.1757***Feat

ALLSPORT CHERRY SLAM: *(ACS=1, PTB=0)*

logprice

= (0.2162-0.0495) -0.0018*SPRING + 0.0053*SUMMER + 0.0279*WINTER + 0.0002*STORE – 0.1757*Feat

= **0.1667** -0.0018*SPRING + 0.0053*SUMMER + 0.0279*WINTER + 0.0002*STORE
– **0.1757***Feat

POWERADE TIDAL BURST: *(ACS=0, PTB=1)*

logprice

= (0.2162-0.0238) - 0.0018*SPRING + 0.0053*SUMMER + 0.0279*WINTER + 0.0002*STORE – 0.1757*Feat

= **0.1924** -0.0018*SPRING + 0.0053*SUMMER + 0.0279*WINTER + 0.0002*STORE
– **0.1757***Feat

Interpretation of the outcome and equations:

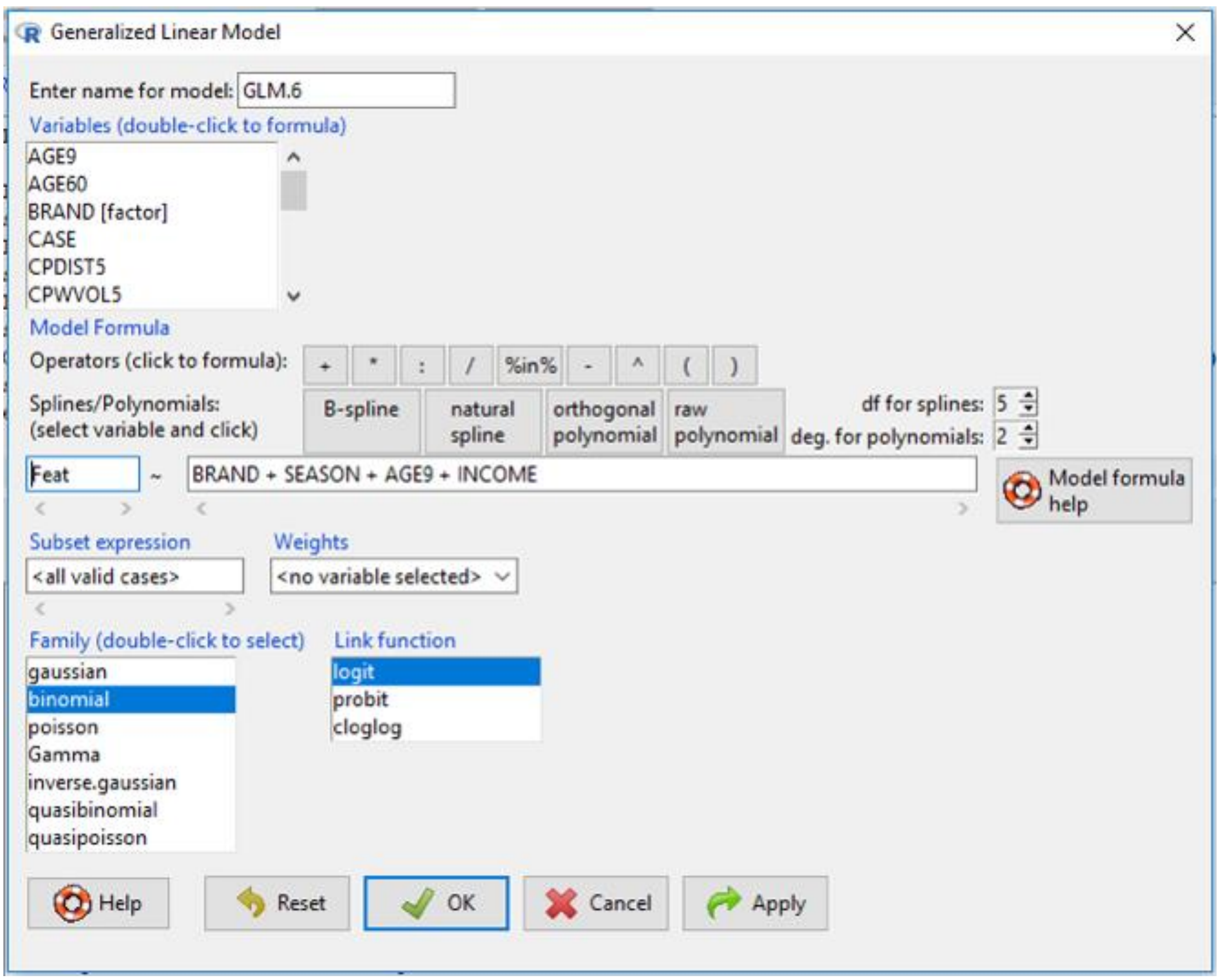
1) Because the coefficient of [Feat] is negative, price decreases if the store is more probable to offer on sale for all brands.

2) The intercept of these brands varies, with ALL has the biggest intercept, PTB has the medium one, and ACS has the least one. Therefore, when the store number remains unchanged, the price of ALL is highest, of PTB is second highest, and of ACS is lowest.
3) Likewise, in the same proportion of on sale, ACS has the lowest price while ALL have the highest price.

➢ **How does the proportion of times a brand is on sale vary across brand?**

When comes to “proportion”, we firstly think about logit. Meanwhile, “on sale” refers to [Feat], which is binary with just two value: 0 and 1. Therefore, we need to use the logit model to explore the relationship between the proportion of times a brand is on sale and the brand itself.

Click: Rcmdr---Statistics---Fit Model---Generalized Linear Model.
And we choose [Feat] as dependent variable, and [BRAND], [SEASON], [AGE9] and [INCOME] as independent variables.



Click [OK] and we got the below outcome:

```
Call:
glm(formula = Feat ~ BRAND + SEASON + AGE9 + INCOME, family = binomial(logit),
    data = Dataset)

Deviance Residuals:
    Min       1Q   Median       3Q      Max
-1.8590  -1.0304   0.6828   0.9789   1.7653

Coefficients:
                              Estimate Std. Error z value   Pr(>|z|)
(Intercept)                    2.69242    0.87585   3.074    0.00211 **
BRAND[T.ALLSPORT CHERRY SLAM]  0.03568    0.07017   0.508    0.61112
BRAND[T.POWERADE TIDAL BURST] -0.29990    0.06415  -4.675 0.00000294 ***
SEASON[T.SPRING]              -0.85937    0.07111 -12.086    < 2e-16 ***
SEASON[T.SUMMER]               0.86770    0.05650  15.357    < 2e-16 ***
SEASON[T.WINTER]              -1.55389    0.08729 -17.801    < 2e-16 ***
AGE9                          -2.87401    1.03444  -2.778    0.00546 **
INCOME                        -0.17604    0.08332  -2.113    0.03462 *
---
Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
```

Using the intercept and coefficients of the outcome, we can get the equations of the three brands.

ALLSPORT LEMON LIME: (ACS=0, PTB=0)

I

=**2.692** -0.859*SPRING + 0.868*SUMMER – 1.554*WINTER – 2.874*AGE9 – 0.176*INCOME

ALLSPORT CHERRY SLAM: (ACS=1, PTB=0)

I

=(**2.692+0.036**) -0.859*SPRING + 0.868*SUMMER – 1.554*WINTER – 2.874*AGE9 – 0.176*INCOME

=**2.728** -0.859*SPRING + 0.868*SUMMER – 1.554*WINTER – 2.874*AGE9 – 0.176*INCOME

POWERADE TIDAL BURST: (ACS=0, PTB=1)

I

=(**2.692-0.300**) -0.859*SPRING + 0.868*SUMMER – 1.554*WINTER – 2.874*AGE9 – 0.176*INCOME

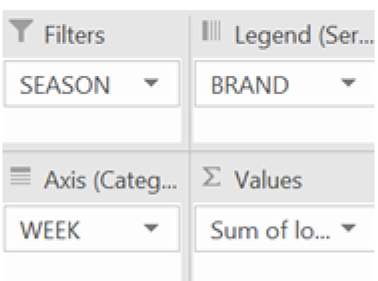
=**2.392** -0.859*SPRING + 0.868*SUMMER – 1.554*WINTER – 2.874*AGE9 – 0.176*INCOME

Interpretations of the outcome and equations:

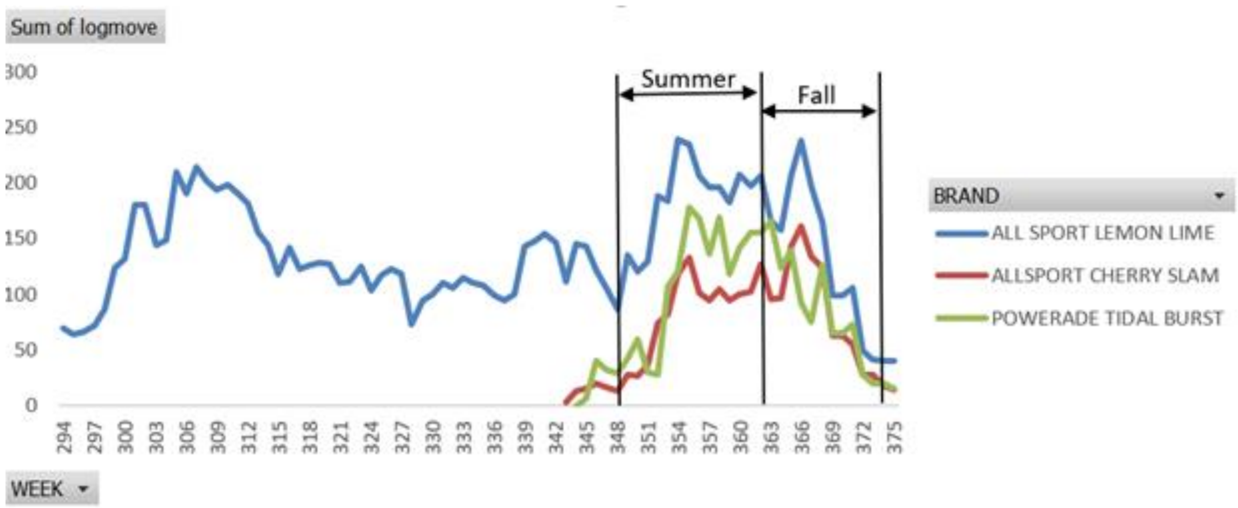
1) Because the coefficient of [INCOME] is negative, the probability of Feat = 1 (brand offered on sale) decreases if the store is in a higher income area.
2) Different brand has different intercepts. The intercept of ACS is the biggest, that of ALL is medium, and that of PTB is the least. Thus, for the same level of income, ACS is most likely, ALL is second most likely, and PTB is least likely to be on sale.
3) As shown in the outcome, the P value of most factors have three stars while some have just two or one stars, which means that most factors are significant at at least a 95% level.

➢ **How does the demands for the three brands vary over time?**

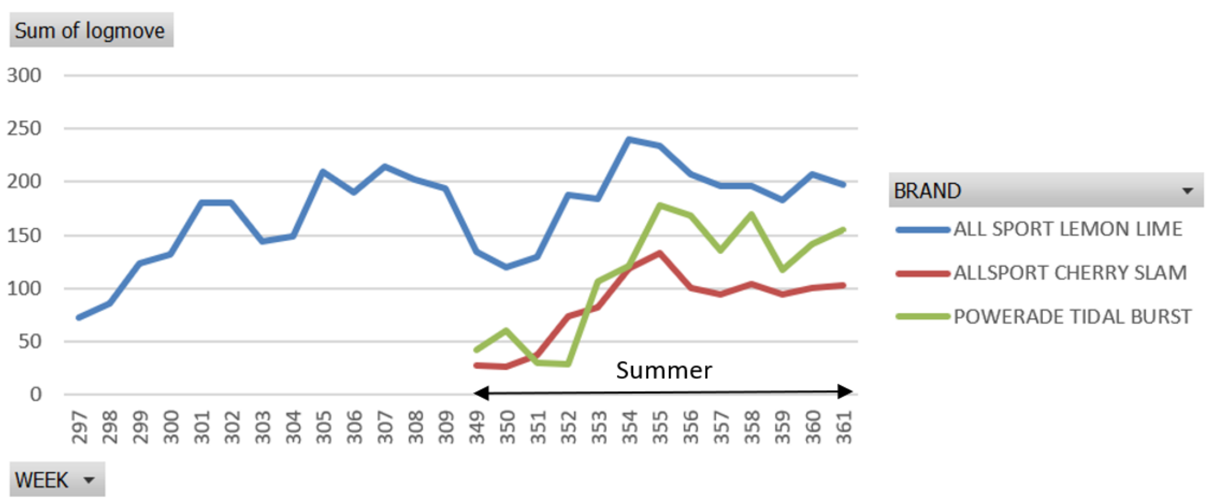
To solve this problem, the simplest way we can think of is through "Pivot Table". We dragged Brand to Legend, Week to Axis, logmove to Values, and Season to Filters.



We generated a line graph to analyze the demands for the three brands over time. Since there was no sale for All Sport Cherry Slam and Power Tidal Burst during 1995, we only focus on the sale from week 342 to week 375. Generally, sales of All Sport Lemon Lime was the highest during the whole period. Overall, for all the three brands, the major demands for sports drinks occurred in summer and fall. Noticeably there were 2 demand peaks for All Sport Lemon Lime and All Sport Cherry Slam.



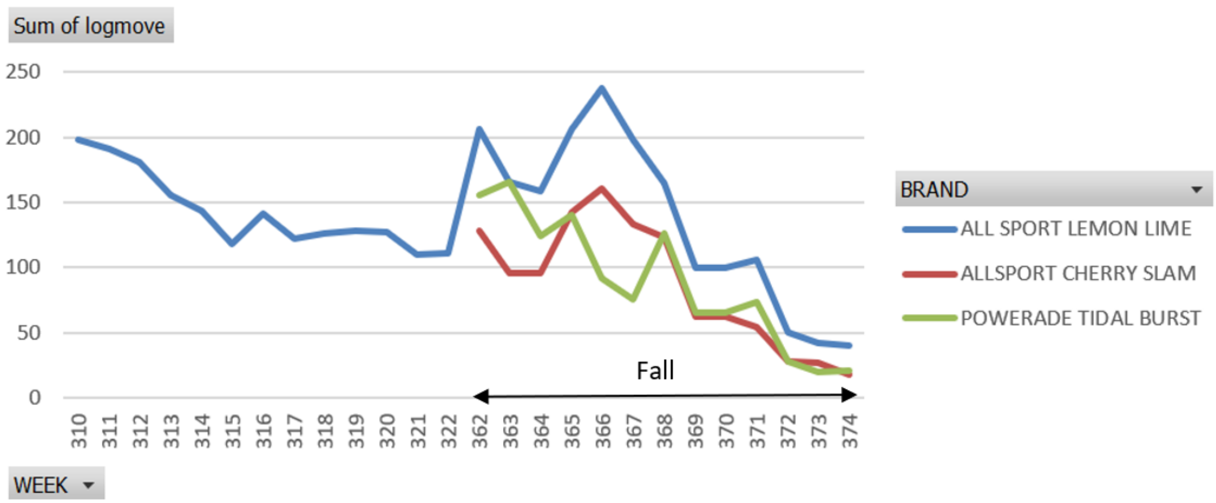
When we specifically studied the summer period, we found the highest demand occurred during week 354 and 355. Because the Independence Day was in the week 356, it is reasonable to assume that the big promotion motivated the desire for shopping and outdoor activities. Consequently, there was a boom in sales of sports drinks.



354	06/20/96	06/26/96	
355	06/27/96	07/03/96	
356	07/04/96	07/10/96	4th of July

The peak demand in fall was from week 364 to 366, which was also likely due to the holiday effect (Labor Day). Sales for All Sport Lemon Lime reached approximately 240 units, and sales for All Sport Cherry Slam approached 160 units. Demands started to decrease from mid-fall mainly because the winter was coming and people were less willing to do sports activities. Basically, demand for sports drinks are affected by season and by holidays during the year. Besides, sports events held in Chicago made a huge difference to the demand for sports drinks.

For example, the famous 1995-1996 Chicago Bulls winning NBA central division boosted the demand for sports drinks in Chicago area.



364	08/29/96	09/04/96	Labor Day
365	09/05/96	09/11/96	

➢ **Develop a model, and test how it performs on a validation sample. For example, you can break your data randomly into two parts, estimation sample and validation sample, using Access (standard practice is to use two-thirds as the estimation sample, and other one-third as the validation sample). Estimate the model using the estimation sample, and assess how well the model predicts the dependent variable(s) in the validation sample.**

For this, we first created a randomIndex variable, which creates a random index by sampling the Sports Drinks subset. We use this random index to create cut points. We then divide the subset into two parts using the cutpoints:

1. Training/Estimation dataset
2. Testing/Validation dataset

The training dataset consists of 2/3rd of entire subset data, while the remaining 1/3rd comprises the testing dataset.

```
> randIndex <- sample(1:dim(SportsDrinks)[1])
> train_cutpoint2_3 <- floor((2*dim(SportsDrinks)[1])/3)
> testCutpoint <- dim(SportsDrinks)[1]-(train_cutpoint2_3+1)
> trainData <- SportsDrinks[randIndex[1:train_cutpoint2_3],]
> testData <- SportsDrinks[randIndex[train_cutpoint2_3+1:testCutpoint],]
```

We then created a linear model for the training dataset, by taking logmove as the dependent variable and the remaining variables as independent variables:

```
> LMtrainData <- lm(logmove ~ AGE9 + AGE60 + BRAND + EDUC + ETHNIC + Feat + HHLARGE + HHSINGLE + HVAL150 + INCOME + logprice + NOCAR + NWHITE + POVERTY + REM + RETIRED  + SEASON + SINGLE +
+   STOREWEEK + UNEMP + WORKWOM + BRAND * logprice, data=trainData)
```

We then predict the testing dataset using the above model as follows:

```
> predict(LMtrainData,testData) -> a
> View(a)
```

Data: a

	row.names	x
1	556	2.3276207
2	7244	1.3021870
3	2415	2.1353120
4	7305	1.7525908
5	7818	1.7026336
6	2664	2.7393324
7	8129	1.5761021
8	8271	1.9397701
9	3953	1.2454479
10	7707	1.7888413
11	3053	1.6197723
12	2392	2.7861518
13	6030	2.0607570
14	4118	1.4794873
15	7421	2.0522302
16	5183	2.0776921
17	3829	2.2759121
18	1475	2.4530743
19	6637	2.3952870

We then formed a comparison table which shows the actual values of ‘logmove’ in the test dataset and the model predicted values of ‘logmove’ of the testing dataset.

```
> compTable <- data.frame(testData[,11],a)
```

```
> colnames(compTable) <- c('test','pred')
> View(compTable)
```

Data: compTable

	row.names	test	pred
1	556	2.3978953	2.3276207
2	7244	1.0986123	1.3021870
3	2415	1.0986123	2.1353120
4	7305	1.7917595	1.7525908
5	7818	1.3862944	1.7026336
6	2664	2.3025851	2.7393324
7	8129	2.7080502	1.5761021
8	8271	2.0794415	1.9397701
9	3953	0.0000000	1.2454479
10	7707	0.0000000	1.7888413
11	3053	0.0000000	1.6197723
12	2392	3.0910425	2.7861518
13	6030	2.1972246	2.0607570
14	4118	0.0000000	1.4794873
15	7421	2.9957323	2.0522302
16	5183	2.1972246	2.0776921
17	3829	2.6390573	2.2759121
18	1475	2.6390573	2.4530743
19	6637	3.5553481	2.3952870

To understand the accuracy of the prediction model, we calculated the error of each predicted logmove value as follows:

```
> compTable$error <- compTable$test - compTable$pred
> View(compTable)
```

	row.names	test	pred	error
1	556	2.3978953	2.3276207	0.07027459570
2	7244	1.0986123	1.3021870	-0.20357472011
3	2415	1.0986123	2.1353120	-1.03669971551
4	7305	1.7917595	1.7525908	0.03916871697
5	7818	1.3862944	1.7026336	-0.31633920779
6	2664	2.3025851	2.7393324	-0.43674730829
7	8129	2.7080502	1.5761021	1.13194808347
8	8271	2.0794415	1.9397701	0.13967141380
9	3953	0.0000000	1.2454479	-1.24544793559
10	7707	0.0000000	1.7888413	-1.78884125642
11	3053	0.0000000	1.6197723	-1.61977234277
12	2392	3.0910425	2.7861518	0.30489065370
13	6030	2.1972246	2.0607570	0.13646760756
14	4118	0.0000000	1.4794873	-1.47948728324
15	7421	2.9957323	2.0522302	0.94350202586
16	5183	2.1972246	2.0776921	0.11953247620
17	3829	2.6390573	2.2759121	0.36314523764
18	1475	2.6390573	2.4530743	0.18598300930
19	6637	3.5553481	2.3952870	1.16006105256

Conclusion: Based on the above analysis, we can see how the current linear model estimated on the training dataset, has predicted the ‘logmove’ values of the testing dataset. We can further calculate the accuracy of each prediction. For example: the model predicted the first row of validation sample with 93% accuracy.
To further enhance the prediction accuracy of the overall model, we can calculate the cumulative error percentage of all the rows, and then try to decrease the error percentage by trying different combinations of independent variables in the linear model (used for estimating the training dataset).

Thus, a best fitting model can be created and used for predicting demand for different brands of sports drinks.