university of groningen

Sales Evolution of Beer Brands

Statistical Learning in Marketing | EBM 214A05.2020-2021.1A

Assignment 2 | Traditional and Modern Time Series Analysis

Group: Group 2.2.

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A First Glance

Two plots of the **sales evolution** of Brand 1 and Brand 3 in year 1:3 (below), and a combination of both over 4 years (right).

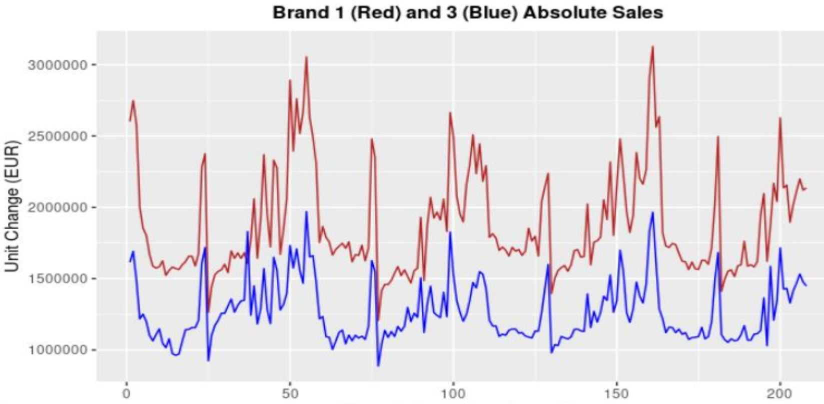
Brand 1 dominates Brand 3 in terms of weekly average sales (1,886,841 EU > 1,273,445 EU)

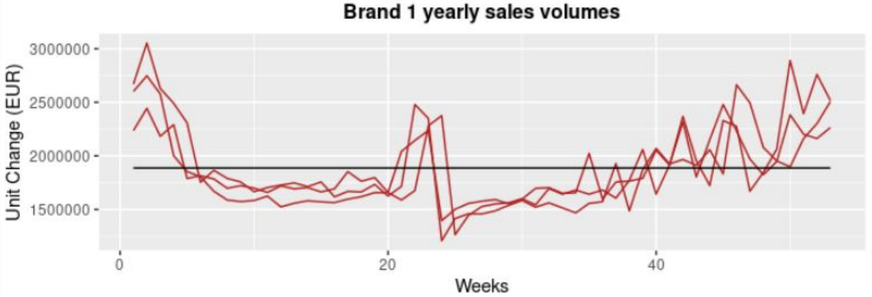
Over 4 years, this is a yearly recurring pattern for both brands, implying **seasonality.**

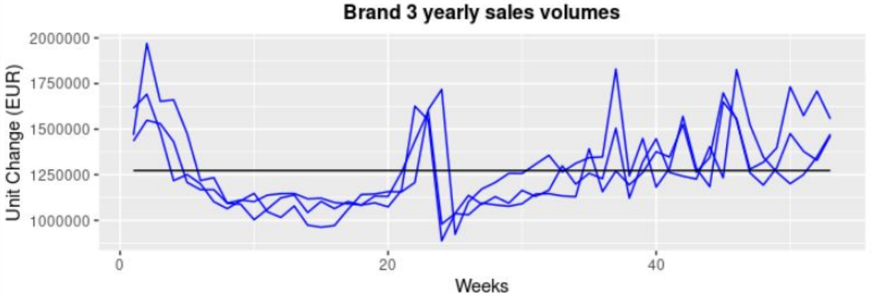
Both are relatively popular during two weeks in June, yoyoing in fall, and very popular in **winter**.

ADF, PP, and KPSS tests for both sales series provide evidence in favour of mean-stationarity, i.e. sales always return to a **historical mean.** (*Appendix 1, 2, 3*)

These results are in line with expectations for top brands in saturated markets. This implies that **one's gain is another's loss.**







Type of Series

→ ACF of **Brand 1** shows gradual decay and PACF shows one spike. This suggests an autoregressive process with order 1. See *Appendix 4* for all outputs.

→ Auto.ARIMA confirms ARIMA(1, 0, 0).

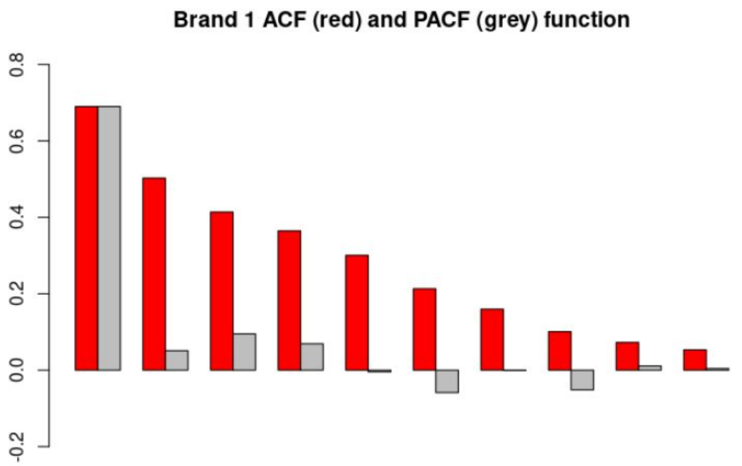
→ **70%** of the sales depend on the sales of previous period. This implies that passed sales volumes are valuable in predicting future sales volumes.

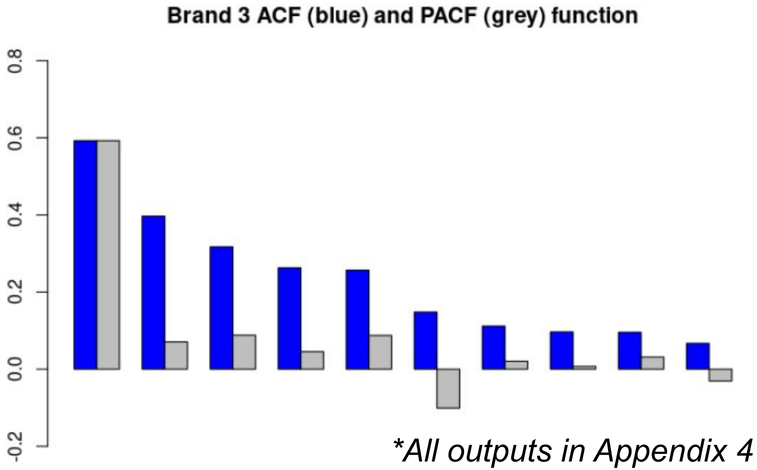
Brand 3 shows a lesser consistent decay in ACF values, implying a potential moving average 1 process. The steep spike in PACF implies the presence of an AR(1) process.

→ Auto.ARIMA confirms ARIMA(1, 0, 1).

→ **72%** of the sales depend on the sales of previous period.

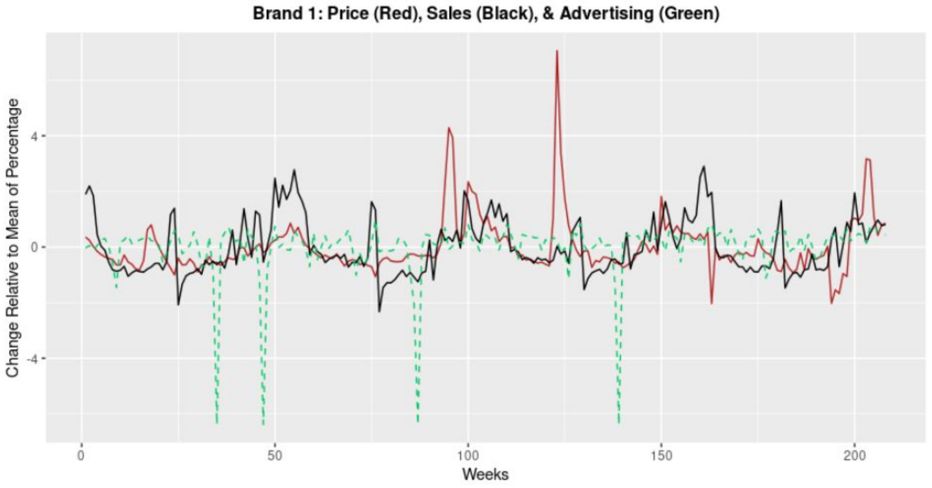
→ The MA coefficient is **-0.2**. Therefore, when there is a sudden increase in sales, this will reduce sales in the next period by 20%. Contrarily, when there is a sudden decrease in sales, this will improve sales in the next period by 20%. This effect disappears after one period.

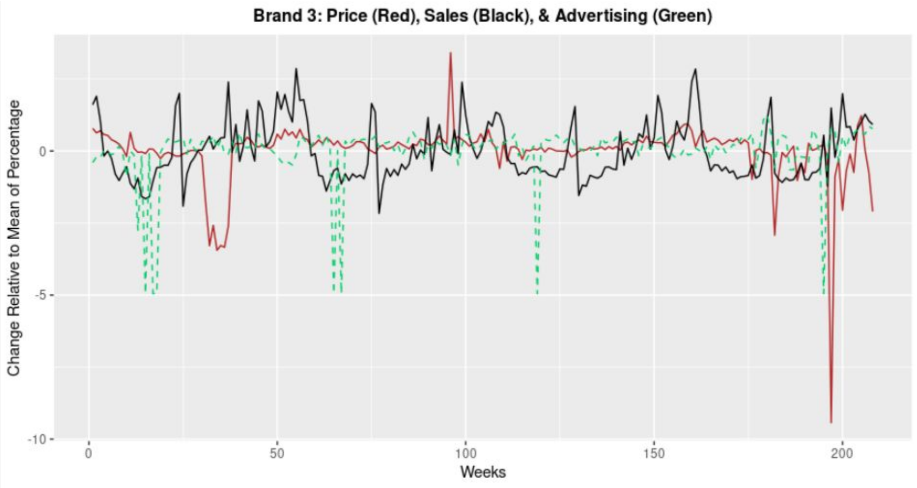




*All outputs in Appendix 4

Time Series and Description of Variables





Price and Sales of **Brand 1** move in similar directions, suggesting a potentially sales-based pricing policy. The brand tends to know in which months customers consume more (less) beer and increase (decrease) prices there.

Advertising dips occur approximately around the same weeks as sales dips. This could be a premeditated measure for market shrinkage.

Brand 3 sales volume seasonality pattern is similar to brand 1.

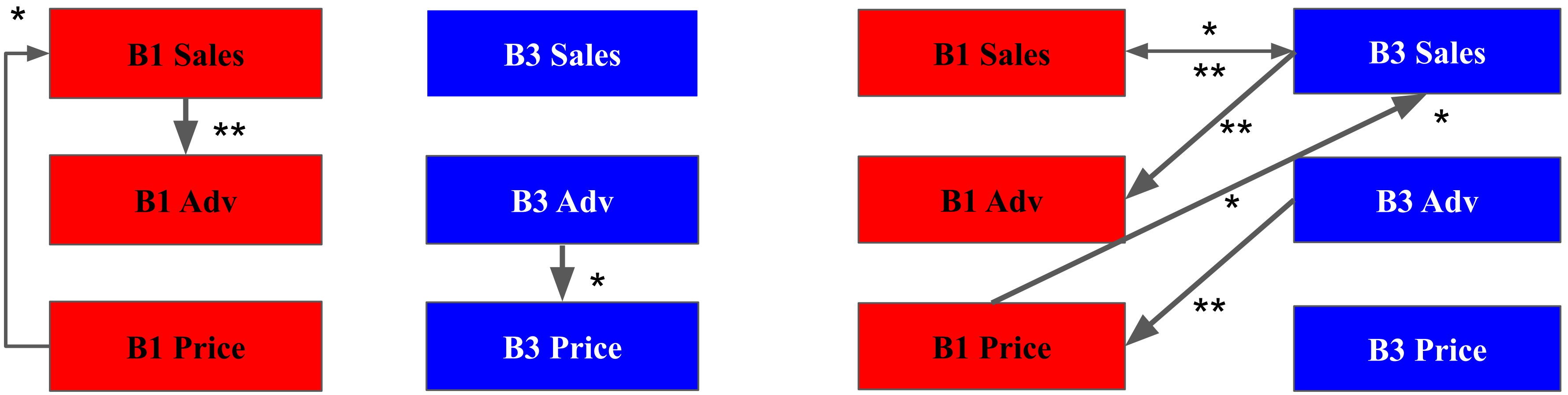
Pricing appears to be more stoic compared to brand 1, indicating potentially diverging pricing strategies among brands.

Advertising dips happen around weeks with lower sales volumes. Moreover, they always happen earlier in the year than brand 1's dips.

Granger-Causality tests

* *10% significance level*
** *5% significance level*

*Granger-Causality **within** the Brands* — *Granger-Causality **between** the Brands*



Marketing variables of B1 are associated with variables of B3, but not the other way around to the same extent. This is makes sense considering previous findings on B1's more dynamic pricing series. In a general sense, these findings raise the conjecture that B1 is more reactionary than B1. Also, reactionary behaviour is never found to be done through the same instruments. The previous conjecture that B1 advertising may be related to B3 advertising is questionable as no g-causation appears to be present.

Because B1 sales granger-causes B1 advertising, it makes sense that B3 sales will also temporarily impact B1 advertising as sales of both brands are related. This is a reminder that although statistical evidence is found for the criteria *time order* and *association*, in absence of a clear view of covariation within the system the question of true causality remains unanswered.

All outputs in Appendix 5 - 9

Stationarity Tests and Specification of VAR Model

The performance variable series are **mean-stationary** and **non-cointegrated**, so there will not be a lasting impact from marketing variables on performance variables. This so-called **business as usual** scenario suits the context of two leading brands in a saturated consumer goods market. (*Appendix 10-15)*

One-shot marketing campaigns have only temporary performance effects in this set-up. As both brands have high **market power**, the **power asymmetry** is rather small which means competitor's ability and willingness to response is given at a higher intensity. The beer market can be seen as a market where **impulse buying** of customers is common. The competitive brand will be more motivated to retaliate to marketing activities in order to counter these attacks. (Steenkamp, Nijs, Hanssens, & Dekimpe, 2005)

Specification of VAR Model

→ Exogenous control variables of seasonality (with a sine and cosine function), trend, feature, feature display and display were added to provide more accurate estimates of the focal variables.

→ Lag determination revealed that using 1 lag is optimal based on 3 of 4 tests, including BIC (*Appendix 21*). Symmetrical lags are used.

→ All stationary series are included in levels. Orthogonal shocks are used.

Immediate Impacts of the Variables

The covariance matrix of residuals (*Appendix 16*) is used to calculate the immediate effect for each endogenous variable. The calculated elasticities were stored in a new matrix (*Appendix 17*). It is important to notice that the significance for all effects cannot be determined within this calculation. Specific increases or decreases are not calculated seeing as the dynamic impact of the system is not considered.

Brand 1 increase of:

Sales ⇧ brand 1 advertising
Price ⇧ brand 1 advertising
Price ⇧ brand 3 advertising

If sales increases, brand 1 immediately increases advertising. When price is increased, both brand 1 and 3 immediately increase advertising.

Brand 3 increase of:

Sales ⇧ brand 1 advertising
Sales ⇧ brand 3 advertising
Price ⇩ brand 3 sales
Price ⇩ brand 3 advertising
Price ⇧ brand 1 advertising

If sales increases, brand 1 and brand 3 immediately increase advertising. If price increases, sales and advertising immediately decrease. Increasing price immediately increases advertising of brand 3.

→ When a competitor increases their price, both brands react by increasing their own advertising.
→ When brand 1 increases their price, they also advertise their product more. However, when brand 3 increases their price, they sharply reduce their advertisement for the products.
→ Advertising does not seem to affect performance, which is the case for both brands.
→ Both brands seem to have an advertising budget based on previous sales, as sales influence advertising positively.

Dynamic Impacts of the Variables

The long term effect of a shock to a variable is analyzed using a cumulative IRF with an orthogonal shock, a confidence interval of 90% and a period of 1 quarter are applied. Since the IRF could be anywhere in between the confidence interval, a specific increase is not calculated as such because the estimation would be unreliable. Instead, only the direction of the cumulative effect is considered.

Brand 1 increase of:

Sales ↗ brand 1 advertising
Sales ↗ brand 3 sales
Price ↗ brand 3 price

If sales of brand 1 increase, brand 1 increases advertising in the long term. If sales of brand 1 increase, sales of brand 3 also increase in the long term. When price of brand 1 increases, the price of brand 3 increases in the long term as well. *(Appendix 18 - 19)*

Brand 3 increase of:

Sales ↗ brand 3 advertising
Sales ↘ brand 3 price

If sales of brand 3 increase, brand 3 increases their advertising in the long term. When sales of brand 3 decrease, brand 3 decreases their price in the long term. *(Appendix 20)*

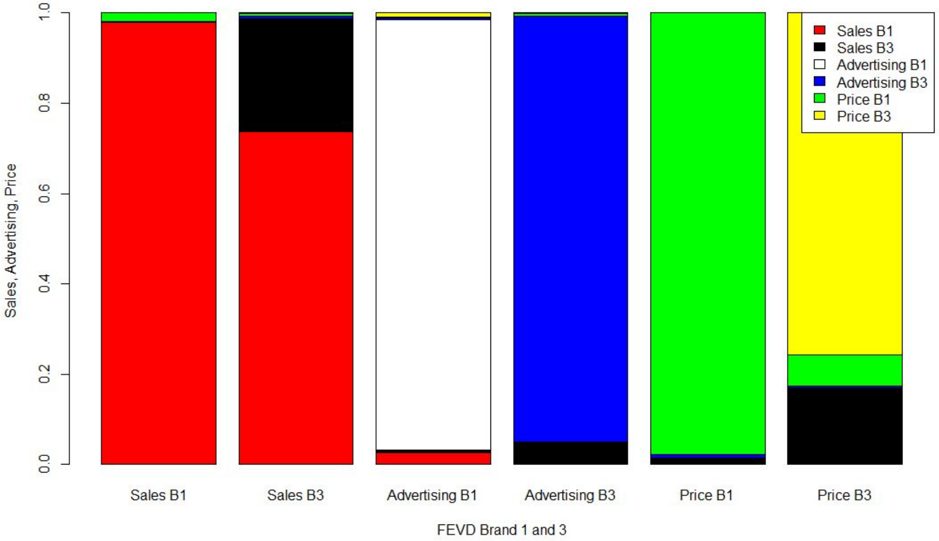
→ There are no long term effects of marketing on performance for either brand.
→ Both brands increase advertising when their sales go up. Sales is therefore a good predictor of future advertising of both brands.
→ Brand 3 seems to lag behind brand 1 in terms of performance. Brand 3 can therefore use sales of brand 1 as a predictor of their own future sales.
→ When brand 1 increases price, brand 3 will react by increasing their price as well.
→ If sales of brand 3 increase, they will decrease price on the long term. Sales of brand 3 can predict future price cuts of brand 3.

FEVD

The FEVD is specified by using periods of one quarter, for up to 6 quarters ahead. The specification of the VAR model that was used to create the FEVD can be seen on slide 5.

The past of:
brand 1 sales have a **74%** share in explaining brand 3 sales
brand 3 sales have a **16%** share in explaining brand 3 price
brand 1 price has a **7%** share in explaining brand 3 price
brand 3 sales have a **5%** share in explaining brand 3 advertising

brand 1 price has a **2%** share in explaining sales of brand 1
brand 1 sales have a **3%** share in explaining advertising of brand 1



→ Brand 3 lags behind brand 1 in terms of sales, seeing as brand 1 sales has a **74%** share in explaining brand 3 sales. Brand 1 sales is therefore an accurate predictor of future sales of brand 3.

→ Brand 1 is mostly predicted by itself. When brand 1 changes price, this has a small effect on their sales. Brand 1 bases their advertising to some extent on their previous sales.

→ Brand 3 reacts more to what is happening in the market than brand 1. Brand 3 base their price for **16%** on their own sales and for **7%** on the brand 1 price. Brand 3 also base their advertising for **5%** on their own sales.

Managerial conclusions

The Narrative

The case is comprised of two larger players in a saturated market with presence of asymmetry in terms of market share and thereby - in a way - power in favor of brand 1 over brand 3. The market follows a consistent seasonal pattern with brief market growth during specific summer months and more extensive market growth in winter months.

Competitive reactions

→ In general, brand 3 reacts more to what is happening in the market than brand 1.
→ However, when the competitor increases the price, both brands react by increasing their own advertising.
→ It is therefore striking that the brands are not responding to a marketing instrument by adjusting the same instrument, but by responding through a different marketing instrument.

Marketing

→ Both advertising and pricing have little effect on the performance of their own brands in the short- and long-term.
→ The brands have different strategies in their marketing mix: When brand 1 increases their price, they also advertise their product more. However, when brand 3 increases their price, they sharply reduce their advertisement for the products.

Predictors of future market behavior

→ Brand 1 sales is an accurate predictor of future sales of brand 3.
→ If sales of brand 3 increase, they will decrease price in the long term. Sales of brand 3 can predict future price-cuts of brand 3.
→ Both brands increase advertising when their sales go up. Sales is therefore a good predictor for future advertising of both brands.

Managerial recommendations

Implications for the Business-as-usual Scenario

Promotions in advertising and price generally do not have a lasting impact on sales in business-as-usual scenarios. Short-term gains associated with such promotions are likely followed up by dips in sales if those promotions impacted only the inherent customer base as overall consumption will likely not increase.

Recommendations for Brands 1 and 3

If both players realize that a strategy with high levels of competitive reactionary behaviors will ultimately damage profit of both parties, passive reactionary behaviour is recommended for both parties. However, this assumes both players to have perfect information on each other's 'attacks'. <u>Hence, the ultimate priority lies not per se in disregarding competitive attacks, but rather in disguising them. In that case, the competitor might not react.</u> Another priority is to predict future market behavior as it predicts market behavior of the competitor.

Both brand are especially aggressive in reacting to price changes of the competitor. When either brand changes their price, the competitors often adjust their advertising. Therefore, price changes can hurt both brands and should only be used cautiously.

References

- Steenkamp, J. B. E., Nijs, V. R., Hanssens, D. M., & Dekimpe, M. G. (2005). Competitive reactions to advertising and promotion attacks. Marketing science, 24(1), 35-54.

- Ataman, M. B., Van Heerde, H. J., & Mela, C. F. (2010). The long-term effect of marketing strategy on brand sales. *Journal of Marketing Research*, *47*(5), 866-882.

Appendix 1 - ADF Tests (1)

Brand 1

Type 1: no drift no trend

	lag	ADF	p.value
[1,]	0	-1.207	0.247
[2,]	1	-1.089	0.289
[3,]	2	-0.915	0.351
[4,]	3	-0.657	0.444

Type 2: with drift no trend

	lag	ADF	p.value
[1,]	0	-6.21	0.01
[2,]	1	-5.53	0.01
[3,]	2	-4.72	0.01
[4,]	3	-4.00	0.01

Type 3: with drift and trend

	lag	ADF	p.value
[1,]	0	-6.23	0.01
[2,]	1	-5.57	0.01
[3,]	2	-4.77	0.01
[4,]	3	-4.05	0.01

Note: in fact, p.value = 0.01 means p.value <= 0.01

Brand 3

Type 1: no drift no trend

	lag	ADF	p.value
[1,]	0	-1.137	0.272
[2,]	1	-0.937	0.343
[3,]	2	-0.699	0.429
[4,]	3	-0.476	0.507

Type 2: with drift no trend

	lag	ADF	p.value
[1,]	0	-7.27	0.01
[2,]	1	-6.10	0.01
[3,]	2	-5.05	0.01
[4,]	3	-4.40	0.01

Type 3: with drift and trend

	lag	ADF	p.value
[1,]	0	-7.25	0.01
[2,]	1	-6.08	0.01
[3,]	2	-5.04	0.01
[4,]	3	-4.38	0.01

Note: in fact, p.value = 0.01 means p.value <= 0.01

Appendix 2 - PP Tests (1)

Brand 1

```
Type 1: no drift no trend
 lag Z_rho p.value
   4 -1.39   0.455
-----
 Type 2: with drift no trend
 lag Z_rho p.value
   4 -60.1    0.01
-----
 Type 3: with drift and trend
 lag Z_rho p.value
   4   -60    0.01
---------------
Note: p-value = 0.01 means p.value <= 0.01
```

Brand 3

```
Type 1: no drift no trend
 lag Z_rho p.value
   4 -1.05   0.484
-----
 Type 2: with drift no trend
 lag Z_rho p.value
   4 -82.1    0.01
-----
 Type 3: with drift and trend
 lag Z_rho p.value
   4 -81.9    0.01
---------------
Note: p-value = 0.01 means p.value <= 0.01
```

Appendix 3 - KPSS Tests (1)

Brand 1

Type 1: no drift no trend

```
 lag  stat p.value
   3 0.575     0.1
-----
 Type 2: with drift no trend
 lag   stat p.value
   3 0.0942     0.1
-----
 Type 1: with drift and trend
 lag   stat p.value
   3 0.0548     0.1
-----------
Note: p.value = 0.01 means p.value <= 0.01
    : p.value = 0.10 means p.value >= 0.10
```

Brand 3

Type 1: no drift no trend

```
 lag  stat p.value
   3 0.644     0.1
-----
 Type 2: with drift no trend
 lag   stat p.value
   3 0.0634     0.1
-----
 Type 1: with drift and trend
 lag   stat p.value
   3 0.0658     0.1
-----------
Note: p.value = 0.01 means p.value <= 0.01
    : p.value = 0.10 means p.value >= 0.10
```

Appendix 4 - Auto.Arima

Brand 1
Best model: ARIMA(1,0,0) with non-zero mean

Series: tsBeerSel1
ARIMA(1,0,0) with non-zero mean

Coefficients:

	ar1	mean
	0.7019	1886840.80
s.e.	0.0498	60019.45

sigma^2 estimated as 6.872e+10: log likelihood=-2889.62
AIC=5785.23 AICc=5785.35 BIC=5795.24

Brand 3
Best model: ARIMA(1,0,1) with non-zero mean

Series: tsBeerSel3
ARIMA(1,0,1) with non-zero mean

Coefficients:

	ar1	ma1	mean
	0.7232	-0.1959	1273444.62
s.e.	0.0906	0.1354	33785.22

sigma^2 estimated as 2.902e+10: log likelihood=-2799.37
AIC=5606.73 AICc=5606.93 BIC=5620.08

Appendix 5 - Granger-Causality Tests within Brand 1

Test result for Sales granger-caused by Price

```
Model 1: Beer_Data$B1_lnSal ~ Lags(Beer_Data$B1_lnSal, 1:13) + Lags(Beer_Data$B1_lnPrice, 1:13)
Model 2: Beer_Data$B1_lnSal ~ Lags(Beer_Data$B1_lnSal, 1:13)
  Res.Df  Df      F     Pr(>F)
1    168
2    181  -13 1.6074 0.0873 .
---
Signif. codes:  0 ‘***’ 0.001 ‘**’ 0.01 ‘*’ 0.05 ‘.’ 0.1 ‘ ’ 1
```

Test result for Advertising granger-caused by Sales

```
Model 1: Beer_Data$B1_lnAdv ~ Lags(Beer_Data$B1_lnAdv, 1:13) + Lags(Beer_Data$B1_lnSal, 1:13)
Model 2: Beer_Data$B1_lnAdv ~ Lags(Beer_Data$B1_lnAdv, 1:13)
  Res.Df  Df     F   Pr(>F)
1    168
2    181 -13 2.688 0.00185 **
---
Signif. codes:  0 ‘***’ 0.001 ‘**’ 0.01 ‘*’ 0.05 ‘.’ 0.1 ‘ ’ 1
```

Appendix 6 - Granger-Causality Tests within Brand 3

Test result for Price granger-caused by Advertising

Model 1: Beer_Data$B3_lnPrice ~ Lags(Beer_Data$B3_lnPrice, 1:13) + Lags(Beer_Data$B3_lnAdv, 1:13)

Model 2: Beer_Data$B3_lnPrice ~ Lags(Beer_Data$B3_lnPrice, 1:13)

	Res.Df	Df	F	Pr(>F)	
1	168				
2	181	-13	1.6723	0.07094	.

Signif. codes: 0 ‘***’ 0.001 ‘**’ 0.01 ‘*’ 0.05 ‘.’ 0.1 ‘ ’ 1

Appendix 7 - Granger-Causality Tests between Brands

Test result for Brand 1 Sales granger-caused by Brand 3 Sales

```
Model 1: Beer_Data$B1_lnSal ~ Lags(Beer_Data$B1_lnSal, 1:13) + Lags(Beer_Data$B3_lnSal, 1:13)
Model 2: Beer_Data$B1_lnSal ~ Lags(Beer_Data$B1_lnSal, 1:13)
  Res.Df  Df      F    Pr(>F)
1    168
2    181 -13 1.6464 0.07712 .
---
Signif. codes:  0 ‘***’ 0.001 ‘**’ 0.01 ‘*’ 0.05 ‘.’ 0.1 ‘ ’ 1
```

Test result for Brand 1 Advertising granger-caused by Brand 3 Sales

```
Model 1: Beer_Data$B1_lnAdv ~ Lags(Beer_Data$B1_lnAdv, 1:13) + Lags(Beer_Data$B3_lnSal, 1:13)
Model 2: Beer_Data$B1_lnAdv ~ Lags(Beer_Data$B1_lnAdv, 1:13)
  Res.Df  Df      F     Pr(>F)
1    168
2    181 -13 1.8907 0.03424 *
---
Signif. codes:  0 ‘***’ 0.001 ‘**’ 0.01 ‘*’ 0.05 ‘.’ 0.1 ‘ ’ 1
```

Appendix 8 - Granger-Causality Tests between Brands

Test result for Brand 3 Sales granger-caused by Brand 1 Sales

```
Model 1: Beer_Data$B3_lnSal ~ Lags(Beer_Data$B3_lnSal, 1:13) + Lags(Beer_Data$B1_lnSal, 1:13)
Model 2: Beer_Data$B3_lnSal ~ Lags(Beer_Data$B3_lnSal, 1:13)
  Res.Df  Df      F     Pr(>F)
1    168
2    181 -13 1.7779 0.05015 .
---
Signif. codes:  0 ‘***’ 0.001 ‘**’ 0.01 ‘*’ 0.05 ‘.’ 0.1 ‘ ’ 1
```

Test result for Brand 3 Sales granger-caused by Brand 1 Price

```
Model 1: Beer_Data$B3_lnSal ~ Lags(Beer_Data$B3_lnSal, 1:13) + Lags(Beer_Data$B1_lnPrice, 1:13)
Model 2: Beer_Data$B3_lnSal ~ Lags(Beer_Data$B3_lnSal, 1:13)
  Res.Df  Df      F  Pr(>F)
1    168
2    181 -13 1.7234 0.06007 .
---
Signif. codes:  0 ‘***’ 0.001 ‘**’ 0.01 ‘*’ 0.05 ‘.’ 0.1 ‘ ’ 1
```

Appendix 9 - Granger-Causality Tests between Brands

Test result for Brand 1 Price granger-caused by Brand 3 Advertising

```
Model 1: Beer_Data$B1_lnPrice ~ Lags(Beer_Data$B1_lnPrice, 1:13) + Lags(Beer_Data$B3_lnAdv, 1:13)
Model 2: Beer_Data$B1_lnPrice ~ Lags(Beer_Data$B1_lnPrice, 1:13)
  Res.Df  Df      F    Pr(>F)
1    168
2    181 -13 2.0724 0.01814 *
---
Signif. codes:  0 ‘***’ 0.001 ‘**’ 0.01 ‘*’ 0.05 ‘.’ 0.1 ‘ ’ 1
```

Appendix 10 - ADF Tests Brand 1 Variables

Sales

Type 1: no drift no trend

	lag	ADF	p.value
[1,]	0	-0.1687	0.595
[2,]	1	-0.2077	0.584
[3,]	2	-0.2013	0.586
[4,]	3	-0.0848	0.619

Type 2: with drift no trend

	lag	ADF	p.value
[1,]	0	-6.23	0.01
[2,]	1	-5.46	0.01
[3,]	2	-4.49	0.01
[4,]	3	-3.80	0.01

Type 3: with drift and trend

	lag	ADF	p.value
[1,]	0	-6.26	0.0100
[2,]	1	-5.51	0.0100
[3,]	2	-4.57	0.0100
[4,]	3	-3.87	0.0167

Note: in fact, p.value = 0.01 means p.value <= 0.01

Advertising

Type 1: no drift no trend

	lag	ADF	p.value
[1,]	0	-1.344	0.198
[2,]	1	-0.941	0.342
[3,]	2	-0.684	0.434
[4,]	3	-0.499	0.500

Type 2: with drift no trend

	lag	ADF	p.value
[1,]	0	-11.14	0.01
[2,]	1	-9.47	0.01
[3,]	2	-8.29	0.01
[4,]	3	-7.13	0.01

Type 3: with drift and trend

	lag	ADF	p.value
[1,]	0	-11.32	0.01
[2,]	1	-9.70	0.01
[3,]	2	-8.57	0.01
[4,]	3	-7.45	0.01

Note: in fact, p.value = 0.01 means p.value <= 0.01

Price

Type 1: no drift no trend

	lag	ADF	p.value
[1,]	0	-0.06375	0.625
[2,]	1	-0.04350	0.631
[3,]	2	-0.00573	0.642
[4,]	3	0.05591	0.660

Type 2: with drift no trend

	lag	ADF	p.value
[1,]	0	-6.03	0.01
[2,]	1	-6.10	0.01
[3,]	2	-5.57	0.01
[4,]	3	-4.47	0.01

Type 3: with drift and trend

	lag	ADF	p.value
[1,]	0	-6.09	0.01
[2,]	1	-6.17	0.01
[3,]	2	-5.64	0.01
[4,]	3	-4.54	0.01

Note: in fact, p.value = 0.01 means p.value <= 0.01

Appendix 11 - ADF Tests Brand 3 Variables

Sales

Type 1: no drift no trend

	lag	ADF	p.value
[1,]	0	-0.1262	0.607
[2,]	1	-0.1482	0.601
[3,]	2	-0.0874	0.618
[4,]	3	0.0349	0.654

Type 2: with drift no trend

	lag	ADF	p.value
[1,]	0	-7.06	0.01
[2,]	1	-5.85	0.01
[3,]	2	-4.84	0.01
[4,]	3	-4.17	0.01

Type 3: with drift and trend

	lag	ADF	p.value
[1,]	0	-7.04	0.01
[2,]	1	-5.84	0.01
[3,]	2	-4.83	0.01
[4,]	3	-4.16	0.01

Note: in fact, p.value = 0.01 means p.value <= 0.01

Advertising

Type 1: no drift no trend

	lag	ADF	p.value
[1,]	0	-1.769	0.0772
[2,]	1	-0.843	0.3772
[3,]	2	-0.641	0.4494
[4,]	3	-0.542	0.4849

Type 2: with drift no trend

	lag	ADF	p.value
[1,]	0	-11.92	0.01
[2,]	1	-6.88	0.01
[3,]	2	-6.03	0.01
[4,]	3	-5.65	0.01

Type 3: with drift and trend

	lag	ADF	p.value
[1,]	0	-12.23	0.01
[2,]	1	-7.11	0.01
[3,]	2	-6.28	0.01
[4,]	3	-5.93	0.01

Note: in fact, p.value = 0.01 means p.value <= 0.01

Price

Type 1: no drift no trend

	lag	ADF	p.value
[1,]	0	-0.269	0.566
[2,]	1	-0.289	0.561
[3,]	2	-0.318	0.552
[4,]	3	-0.306	0.556

Type 2: with drift no trend

	lag	ADF	p.value
[1,]	0	-8.77	0.01
[2,]	1	-6.33	0.01
[3,]	2	-4.81	0.01
[4,]	3	-4.73	0.01

Type 3: with drift and trend

	lag	ADF	p.value
[1,]	0	-8.78	0.01
[2,]	1	-6.33	0.01
[3,]	2	-4.81	0.01
[4,]	3	-4.74	0.01

Note: in fact, p.value = 0.01 means p.value <= 0.01

Appendix 12 - PP Tests Brand 1 Variables

Sales
Type 1: no drift no trend
lag Z_rho p.value
4 -0.0182 0.686

Type 2: with drift no trend
lag Z_rho p.value
4 -60.4 0.01

Type 3: with drift and trend
lag Z_rho p.value
4 -60.5 0.01

Note: p-value = 0.01 means p.value <= 0.01

Advertising
Type 1: no drift no trend
lag Z_rho p.value
4 -1.11 0.479

Type 2: with drift no trend
lag Z_rho p.value
4 -146 0.01

Type 3: with drift and trend
lag Z_rho p.value
4 -146 0.01

Note: p-value = 0.01 means p.value <= 0.01

Price
Type 1: no drift no trend
lag Z_rho p.value
4 -0.00299 0.69

Type 2: with drift no trend
lag Z_rho p.value
4 -61.2 0.01

Type 3: with drift and trend
lag Z_rho p.value
4 -62.2 0.01

Note: p-value = 0.01 means p.value <= 0.01

Appendix 13 - PP Tests Brand 3 Variables

Sales

Type 1: no drift no trend

```
 lag   Z_rho   p.value
   4 -0.0116   0.688
-----
 Type 2: with drift no trend
 lag Z_rho  p.value
   4 -78.1    0.01
-----
 Type 3: with drift and trend
 lag Z_rho  p.value
   4 -77.9    0.01
---------------
```

Note: p-value = 0.01 means p.value <= 0.01

Advertising

Type 1: no drift no trend

```
 lag Z_rho p.value
   4 -1.83   0.419
-----
 Type 2: with drift no trend
 lag Z_rho  p.value
   4  -198    0.01
-----
 Type 3: with drift and trend
 lag Z_rho  p.value
   4  -203    0.01
---------------
```

Note: p-value = 0.01 means p.value <= 0.01

Price

Type 1: no drift no trend

```
 lag   Z_rho p.value
   4 -0.0346   0.683
-----
 Type 2: with drift no trend
 lag Z_rho p.value
   4  -125    0.01
-----
 Type 3: with drift and trend
 lag Z_rho p.value
   4  -126    0.01
---------------
```

Note: p-value = 0.01 means p.value <= 0.01

Appendix 14 - KPSS Tests Brand 1 Variables

Sales

Type 1: no drift no trend

lag stat p.value

3 0.0384 0.1

Type 2: with drift no trend

lag stat p.value

3 0.112 0.1

Type 1: with drift and trend

lag stat p.value

3 0.0581 0.1

Note: p.value = 0.01 means p.value <= 0.01

: p.value = 0.10 means p.value >= 0.10

Advertising

Type 1: no drift no trend

lag stat p.value

3 1.58 0.0577

Type 2: with drift no trend

lag stat p.value

3 0.349 0.0989

Type 1: with drift and trend

lag stat p.value

3 0.0358 0.1

Note: p.value = 0.01 means p.value <= 0.01

: p.value = 0.10 means p.value >= 0.10

Price

Type 1: no drift no trend

lag stat p.value

3 0.0137 0.1

Type 2: with drift no trend

lag stat p.value

3 0.138 0.1

Type 1: with drift and trend

lag stat p.value

3 0.0763 0.1

Note: p.value = 0.01 means p.value <= 0.01

: p.value = 0.10 means p.value >= 0.10

Appendix 15 - KPSS Tests Brand 3 Variables

Sales

Type 1: no drift no trend

lag stat p.value

3 0.0267 0.1

Type 2: with drift no trend

lag stat p.value

3 0.0664 0.1

Type 1: with drift and trend

lag stat p.value

3 0.0671 0.1

Note: p.value = 0.01 means p.value <= 0.01

: p.value = 0.10 means p.value >= 0.10

Advertising

Type 1: no drift no trend

lag stat p.value

3 3.05 0.01

Type 2: with drift no trend

lag stat p.value

3 0.407 0.0742

Type 1: with drift and trend

lag stat p.value

3 0.072 0.1

Note: p.value = 0.01 means p.value <= 0.01

: p.value = 0.10 means p.value >= 0.10

Price

Type 1: no drift no trend

lag stat p.value

3 0.0443 0.1

Type 2: with drift no trend

lag stat p.value

3 0.219 0.1

Type 1: with drift and trend

lag stat p.value

3 0.207 0.0132

Note: p.value = 0.01 means p.value <= 0.01

: p.value = 0.10 means p.value >= 0.10

Appendix 16 - Covariance Matrix

Covariance matrix of residuals:

	B1_lnSal	B3_lnSal	B1_lnAdv	B3_lnAdv	B1_lnPrice	B3_lnPrice
B1_lnSal	1.430e-02	1.161e-02	0.0355591	0.009737	-6.078e-05	5.762e-05
B3_lnSal	1.161e-02	1.324e-02	0.0198103	0.017765	-8.371e-05	-1.793e-04
B1_lnAdv	3.556e-02	1.981e-02	3.5714307	-0.103819	7.445e-04	6.027e-04
B3_lnAdv	9.737e-03	1.776e-02	-0.1038188	4.464526	1.287e-03	-1.466e-03
B1_lnPrice	-6.078e-05	-8.371e-05	0.0007445	0.001287	1.721e-04	9.065e-06
B3_lnPrice	5.762e-05	-1.793e-04	0.0006027	-0.001466	9.065e-06	6.747e-05

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Appendix 17 - Elasticity Matrix

Elasticities of Immediate Effects:

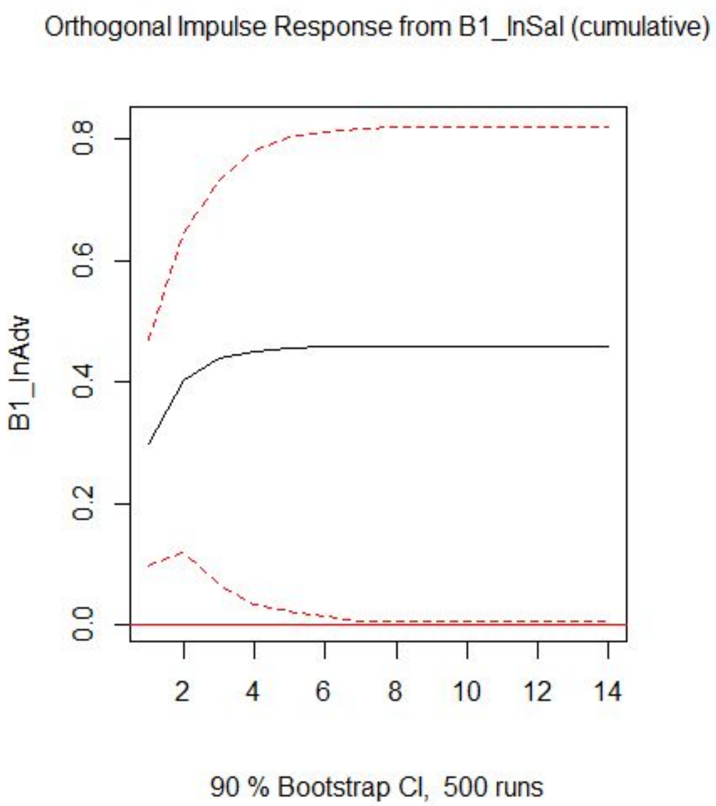
	B1_lnSal	B3_lnSal	B1_lnAdv	B3_lnAdv	B1_lnPrice	B3_lnPrice
B1_lnSal	1	0.8769	0.0010	0.0022	0.3532	0.8540
B3_lnSal	0.81189	1	0.0055	0.0040	-0.4864	-2.6575
B1_lnAdv	2.4867	1.4962	1	-0.0233	4.3260	8.9329
B3_lnAdv	0.6809	1.3414	-0.0291	1	7.4782	-21.7281
B1_lnPrice	-0.0043	-0.0063	0.0002	0.0003	1	0.1344
B3_lnPrice	0.0040	-0.0135	0.0001	-0.0003	0.0001	1

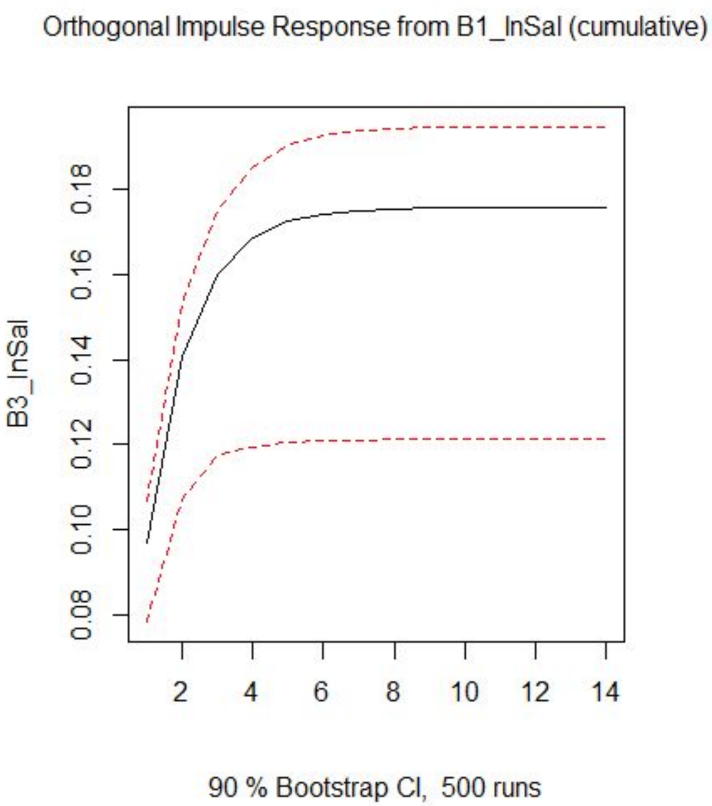
*Values highlighted in green represent **striking positive**, immediate effects.*

*Values highlighted in red represent **striking negative**, immediate effects,*

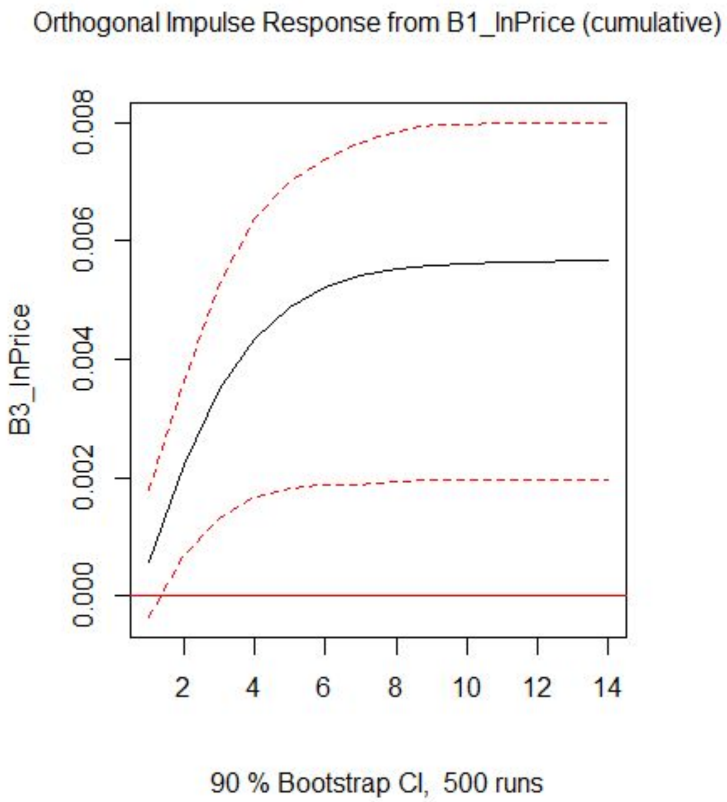
Based on the division of the covariance of residuals, this table provides all the immediate effects of the endogenous variables, presented as elasticities.

Appendix 18 - IRF graphs

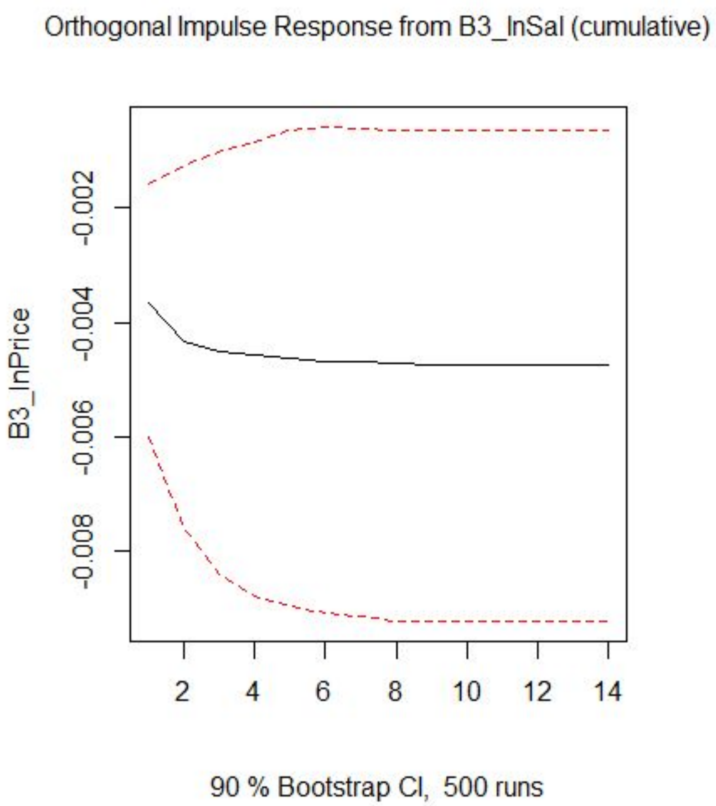


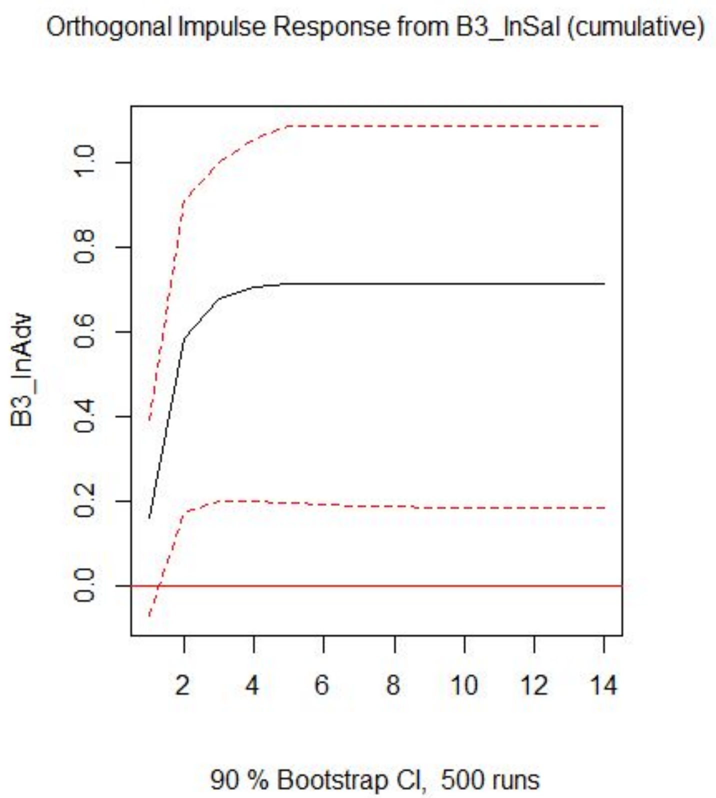


Appendix 19 - IRF graphs



Appendix 20 - IRF graphs





Appendix 21 - VAR selection of lags

```
$selection
AIC(n)  HQ(n)  SC(n) FPE(n)
     2      1      1      1

$criteria
                  1             2             3             4
AIC(n) -2.503663e+01 -2.503752e+01 -2.488219e+01 -2.481628e+01
HQ(n)  -2.432604e+01 -2.409005e+01 -2.369786e+01 -2.339509e+01
SC(n)  -2.327998e+01 -2.269532e+01 -2.195443e+01 -2.130298e+01
FPE(n)  1.342539e-11  1.346470e-11  1.582711e-11  1.706690e-11
```

```
#create backup of data and more convenient name
library(readr)
SLIMBeerData <- read_csv("~/Desktop/SLIM_ASSIGNMENT_1/SLIMBeerData.csv")
View(SLIMBeerData)
Backup_Beer_Data <- SLIMBeerData
Beer_Data <- SLIMBeerData

#required functions
library(ggplot2)
install.packages("xts")
library(xts)
library(reshape2)

#required according to slides
install.packages("astsa")
install.packages("tseries")
install.packages("FitAR")
install.packages("forecast")
install.packages("aTSA")
library(FitAR)
library(forecast)
library(tseries)
library(gplots)
library(aTSA)
library(astsa)
library(lmtest)

#Graphs

first_year <- data.frame(Beer_Data[1:53,]$B1_Sal, Beer_Data[1:53,]$Week)
second_year <- data.frame(Beer_Data[54:106,]$B1_Sal, Beer_Data[54:106,]$Week)
third_year <- data.frame(Beer_Data[107:159,]$B1_Sal, Beer_Data[107:159,]$Week)

bfirst_year <- data.frame(Beer_Data[1:53,]$B3_Sal, Beer_Data[1:53,]$Week)
bsecond_year <- data.frame(Beer_Data[54:106,]$B3_Sal, Beer_Data[54:106,]$Week)
bthird_year <- data.frame(Beer_Data[107:159,]$B3_Sal, Beer_Data[107:159,]$Week)


B3_sal_df <- cbind(bfirst_year, bsecond_year, bthird_year)
B1_sal_df <-cbind(first_year, second_year, third_year)



ggplot(data=B1_sal_df, aes(x=Beer_Data.1.53....Week)) +
  geom_line(aes(y=B1_sal_df$Beer_Data.1.53....B1_Sal), color="firebrick") +
```

```
  geom_line(aes(y=B1_sal_df$Beer_Data.54.106....B1_Sal), color="firebrick") +
  geom_line(aes(y=B1_sal_df$Beer_Data.107.159....B1_Sal), color="firebrick") +
  geom_line(aes(y= 1886841), color="black") +
  ggtitle("Brand 1 yearly sales volumes") +
  theme(plot.title = element_text(size=12, face="bold", hjust = 0.5)) +
  labs(x = "Weeks", y = "Unit Change (EUR)", color = "Legend") +
  scale_color_manual(values = c("firebrick", "black", "blue"))


ggplot(data=B3_sal_df, aes(x=B3_sal_df$Beer_Data.1.53....Week)) +
  geom_line(aes(y=B3_sal_df$Beer_Data.1.53....B3_Sal), color="blue") +
  geom_line(aes(y=B3_sal_df$Beer_Data.54.106....B3_Sal), color="blue") +
  geom_line(aes(y=B3_sal_df$Beer_Data.107.159....B3_Sal), color="blue") +
  geom_line(aes(y= 1273445), color="black") +
  ggtitle("Brand 3 yearly sales volumes") +
  theme(plot.title = element_text(size=12, face="bold", hjust = 0.5)) +
  labs(x = "Weeks", y = "Unit Change (EUR)", color = "Legend") +
  scale_color_manual(values = c("firebrick", "black", "blue"))

#first look at data
head(SLIMBeerData)

#Question 1
    #Question 1.1

#Brand 1 sales plot
plot(Beer_Data$Week, Beer_Data$B1_Sal, type="l", col="red", lwd=5, xlab="weeks",
   ylab="sales", main="Sales Brand 1")
#Brand 3 sales plot
plot(Beer_Data$Week, Beer_Data$B3_Sal, type="l", col="red", lwd=5, xlab="weeks",
   ylab="sales", main="Sales Brand 3")

    #Question 1.2
#Brand 1 sales - stationary

adf.test(Beer_Data$B1_Sal, nlag = 4)
pp.test(Beer_Data$B1_Sal, output = TRUE)
kpss.test(Beer_Data$B1_Sal, output = TRUE)

Beer1ACF = acf(Beer_Data$B1_Sal, lag.max = 10)
Beer1PACF = pacf(Beer_Data$B1_Sal, lag.max = 10)
#if type 1 is significant, basically means nothing going on as the mean would be 0 then
#adf.test shows type 2 is significant, that is mean stationary.
#interpretation: ACF shows slow decay, PACF shows one spike, so probably only an AR process is
going on (shock comes from the y variable)
```

```
#Brand 3 sales - stationary
adf.test(Beer_Data$B3_Sal, nlag = 4)
pp.test(Beer_Data$B3_Sal, output = TRUE)
kpss.test(Beer_Data$B3_Sal, output = TRUE)

Beer3ACF = acf(Beer_Data$B3_Sal, lag.max = 10)
Beer3PACF = pacf(Beer_Data$B3_Sal, lag.max = 10)
#again type 2 is significant, means that it is mean stationary
#interpretation: ACF shows slow decay, PACF shows one spike, so probably only an AR process is going on (shock comes from the y variable)

    #Question 1.3
#What type of ARIMA model best describes the two series?

  #ARIMA for brand 1
BeerSel1 = Beer_Data$B1_Sal
tsBeerSel1 = as.ts(BeerSel1)
Beer1arima <- arima(tsBeerSel1, order = c(1, 0, 0))
coeftest(Beer1arima)

#check whether the results of auto.arima show that order (1, 0, 0) is indeed the best.
auto.arima(tsBeerSel1, test = c("adf"), trace = TRUE)
auto.arima(tsBeerSel1, d = 0, trace = TRUE)
#interpretation: value of phi(?) is 0.70, mean is 1886840.80

  #ARIMA for brand 3
BeerSel3 = Beer_Data$B3_Sal
tsBeerSel3 = as.ts(BeerSel3)
Beer3arima <- arima(tsBeerSel3, order = c(1, 0, 0))
coeftest(Beer3arima)

#check whether the results of auto.arima show that order (1, 0, 0) is indeed the best. It is not, also MA, so (1, 0, 1)
auto.arima(tsBeerSel3, test = c("adf"), trace = TRUE)
auto.arima(tsBeerSel3, d = 0, trace = TRUE)
#interpretation: so we have an AR and an MA process going on, which means that the change of the sales depend both on the sales of previous period (AR)
#and on some random shock from the error component (MA)
#it shows a -0.1959 ma1, this means that 20% of the shock carries over, with a negative effect on sales. This could be a continuing negative effect,
#but also a compensation effect of e.g. a price promotion in the previous period (something positive)

#we have an MA coef of -0.1959, this means that there was a shock from the random component this period which had a certain effect on sales.
```

```r
#this effect is still there next period multiplied by -0.1959. so if shock is +50 this period, then next period it is +50 * -0.1959 = -10 effect on sales next period
#and if shock is -50 this period, then next period it is -50 * -0.1959 = +10 effect on sales next period.
#the period after next period, the shock disappeared again as it came from the random component

#Question 2
    #Question 2.1

#Brand 1 log sales plot
plot(Beer_Data$Week, Beer_Data$B1_lnSal, type="l", col="red", lwd=5, xlab="weeks"
   , ylab="sales log", main="Sales log Brand 1")
#Brand 1 log advertising plot
plot(Beer_Data$Week, Beer_Data$B1_lnAdv, type="l", col="red", lwd=5, xlab="weeks"
   , ylab="advertising log", main="Advertising log Brand 1")
#Brand 1 log price plot
plot(Beer_Data$Week, Beer_Data$B1_lnPrice, type="l", col="red", lwd=5, xlab="weeks"
   , ylab="price log", main="Price log Brand 1")

#Brand 3 log sales plot
plot(Beer_Data$Week, Beer_Data$B3_lnSal, type="l", col="red", lwd=5, xlab="weeks"
   , ylab="sales log", main="Sales log Brand 3")
#Brand 3 log advertising plot
plot(Beer_Data$Week, Beer_Data$B3_lnAdv, type="l", col="red", lwd=5, xlab="weeks"
   , ylab="advertising log", main="Advertising log Brand 3")
#Brand 3 log price plot
plot(Beer_Data$Week, Beer_Data$B3_lnPrice, type="l", col="red", lwd=5, xlab="weeks"
   , ylab="price log", main="Price log Brand 3")



 #Question 2.2

#######Brand 1 Granger causality tests

#H0: no cause

#Advertising is not granger-causing Sales (insignificant!)
grangertest(Beer_Data$B1_lnSal~Beer_Data$B1_lnAdv, order = 13, data = SLIMBeerData)

#Price is granger-causing Sales (insignificant to 5% level but significant to 10% level)
grangertest(Beer_Data$B1_lnSal~Beer_Data$B1_lnPrice, order = 13, data = SLIMBeerData)

#Sales is granger-causing Advertisement (significant p-value = .00185)
grangertest(Beer_Data$B1_lnAdv~Beer_Data$B1_lnSal, order = 13, data = SLIMBeerData)
```

```
#Price is not granger-causing Advertisement (non-significant p-value!)
grangertest(Beer_Data$B1_lnAdv~Beer_Data$B1_lnPrice, order = 13, data = SLIMBeerData)


#Sales is not granger-causing Price (non-significant p-value!)
grangertest(Beer_Data$B1_lnPrice~Beer_Data$B1_lnSal, order = 13, data = SLIMBeerData)


#Advertising is not granger-causing Price (non-significant p-value!)
grangertest(Beer_Data$B1_lnPrice~Beer_Data$B1_lnAdv, order = 13, data = SLIMBeerData)



#######Brand 3 Granger causality tests

#Sales granger caused by advertising: no
grangertest(Beer_Data$B3_lnSal~Beer_Data$B3_lnAdv, order = 13, data = SLIMBeerData)

#Sales granger caused by price: no
grangertest(Beer_Data$B3_lnSal~Beer_Data$B3_lnPrice, order = 13, data = SLIMBeerData)

#Advertising granger caused by sales: no
grangertest(Beer_Data$B3_lnAdv~Beer_Data$B3_lnSal, order = 13, data = SLIMBeerData)

#Advertising granger caused by price: no
grangertest(Beer_Data$B3_lnAdv~Beer_Data$B3_lnPrice, order = 13, data = SLIMBeerData)

#Price granger caused by sales: no
grangertest(Beer_Data$B3_lnPrice~Beer_Data$B3_lnSal, order = 13, data = SLIMBeerData)

#Price granger caused by advertising: yes 10% level
grangertest(Beer_Data$B3_lnPrice~Beer_Data$B3_lnAdv, order = 13, data = SLIMBeerData)


######causality tests Brand 3 on Brand 1

#Sales Brand 1 granger-caused by Sales Brand 3? 10% level
grangertest(Beer_Data$B1_lnSal~Beer_Data$B3_lnSal, order = 13, data = SLIMBeerData)

#Sales Brand 1 granger-caused by Advertising Brand 3? No
grangertest(Beer_Data$B1_lnSal~Beer_Data$B3_lnAdv, order = 13, data = SLIMBeerData)

#Sales Brand 1 granger-caused by Price Brand 3? No
grangertest(Beer_Data$B1_lnSal~Beer_Data$B3_lnPrice, order = 13, data = SLIMBeerData)
```

```
#Advertising Brand 1 granger-caused by Sales Brand 3? Yes 5% level
grangertest(Beer_Data$B1_lnAdv~Beer_Data$B3_lnSal, order = 13, data = SLIMBeerData)

#Advertising Brand 1 granger-caused by Advertising Brand 3? NO
grangertest(Beer_Data$B1_lnAdv~Beer_Data$B3_lnAdv, order = 13, data = SLIMBeerData)

#Advertising Brand 1 granger-caused by Price Brand 3? NO
grangertest(Beer_Data$B1_lnAdv~Beer_Data$B3_lnPrice, order = 13, data = SLIMBeerData)

#Price Brand 1 granger-caused by Sales Brand 3? No
grangertest(Beer_Data$B1_lnPrice~Beer_Data$B3_lnSal, order = 13, data = SLIMBeerData)

#Price Brand 1 granger-caused by Advertising Brand 3? Yes 5%-level
grangertest(Beer_Data$B1_lnPrice~Beer_Data$B3_lnAdv, order = 13, data = SLIMBeerData)

#Price Brand 1 granger-caused by Price Brand 3? No
grangertest(Beer_Data$B1_lnPrice~Beer_Data$B3_lnPrice, order = 13, data = SLIMBeerData)

#######granger-causality tests Brand 1 on Brand 3

#Sales Brand 3 granger-caused by Sales Brand 1? 5% level
grangertest(Beer_Data$B3_lnSal~Beer_Data$B1_lnSal, order = 13, data = SLIMBeerData)

#Sales Brand 3 granger-caused by Advertising Brand 1? No
grangertest(Beer_Data$B3_lnSal~Beer_Data$B1_lnAdv, order = 13, data = SLIMBeerData)

#Sales Brand 3 granger-caused by Price Brand 1? 10%-level
grangertest(Beer_Data$B3_lnSal~Beer_Data$B1_lnPrice, order = 13, data = SLIMBeerData)

#Advertising Brand 3 granger-caused by Sales Brand 1? No
grangertest(Beer_Data$B3_lnAdv~Beer_Data$B1_lnSal, order = 13, data = SLIMBeerData)

#Advertising Brand 3 granger-caused by Advertising Brand 1? No
grangertest(Beer_Data$B3_lnAdv~Beer_Data$B1_lnAdv, order = 13, data = SLIMBeerData)

#Advertising Brand 3 granger-caused by Price Brand 1? No
grangertest(Beer_Data$B3_lnAdv~Beer_Data$B1_lnPrice, order = 13, data = SLIMBeerData)

#Price Brand 3 granger-caused by Sales Brand 1? NO
grangertest(Beer_Data$B3_lnPrice~Beer_Data$B1_lnSal, order = 13, data = SLIMBeerData)

#Price Brand 3 granger-caused by Advertising Brand 1? NO
grangertest(Beer_Data$B3_lnPrice~Beer_Data$B1_lnAdv, order = 13, data = SLIMBeerData)
```

```
#Price Brand 3 granger-caused by Price Brand 1? NO
grangertest(Beer_Data$B3_lnPrice~Beer_Data$B1_lnPrice, order = 13, data = SLIMBeerData)



#Stationarity tests for B1: No unit roots

install.packages("aTSA")
library(aTSA)

  #Sales: No Unit Root -> Stationary
adf.test(Beer_Data$B1_lnSal, nlag = 4, output = TRUE)
pp.test(Beer_Data$B1_lnSal, output = TRUE)
kpss.test(Beer_Data$B1_lnSal, output = TRUE)

  #Advertising ADF and PP say stationary, KPSS most likely also stationary
adf.test(Beer_Data$B1_lnAdv, nlag = 4, output = TRUE)
pp.test(Beer_Data$B1_lnAdv, output = TRUE)
kpss.test(Beer_Data$B1_lnAdv, output = TRUE)

  #Price All say stationary
adf.test(Beer_Data$B1_lnPrice, nlag = 4, output = TRUE)
pp.test(Beer_Data$B1_lnPrice, output = TRUE)
kpss.test(Beer_Data$B1_lnPrice, output = TRUE)

#Stationarity tests for B3

#Sales: All say stationary
adf.test(Beer_Data$B3_lnSal, nlag = 4, output = TRUE)
pp.test(Beer_Data$B3_lnSal, output = TRUE)
kpss.test(Beer_Data$B3_lnSal, output = TRUE)

#Advertising ADF and PP say stationary, KPSS most likely also stationary
adf.test(Beer_Data$B3_lnAdv, nlag = 4, output = TRUE)
pp.test(Beer_Data$B3_lnAdv, output = TRUE)
kpss.test(Beer_Data$B3_lnAdv, output = TRUE)

#Price two say stationary, kpss says unit root?, 2v1 so stationary
adf.test(Beer_Data$B3_lnPrice, nlag = 4, output = TRUE)
pp.test(Beer_Data$B3_lnPrice, output = TRUE)
kpss.test(Beer_Data$B3_lnPrice, output = TRUE)

#so cointegration is not possible, because there are no unit roots!
#Business as usual scenario!
```

```
#Determining which variables are endogenous and which are exogenous
#all control variables are exogenous and all other endogenous

#testing for seasonality!!!
#create sine and cosine
sin.weeks <- sin(Beer_Data$Week/52*2*pi)
cos.weeks <- cos(Beer_Data$Week/52*2*pi)
Beer_Data <- cbind (Beer_Data, sin.weeks, cos.weeks)


#Showing the sine and cosine function to control for seasonal effects
plot(Beer_Data[,c(1)],Beer_Data$sin.weeks, type="l", col="red", lwd=5,
    xlab="weeks", ylab="sinus and cosinus",
    main="Sine (grey) and cosine (red) over time")
lines(Beer_Data$cos.weeks, type="l", col="grey", lwd=5)


#Determining lag length of the endogenous variables
install.packages("vars")
library(vars)

#Exogenous
#Seasonality (sine + cosine)
#Distribution B1 and B3
#Feature B1 and B3
#Display B1 and B3
#Feature + display B1 and B3

#Endogenous
#Sales B1 and B3
#Advertising B1 and B3
#Price B1 and B3

#Determining lag length of the endogenous variables
Beer_Data_Endo = Beer_Data[, c('B1_lnSal', 'B3_lnSal', 'B1_lnAdv', 'B3_lnAdv',
                        'B1_lnPrice', 'B3_lnPrice')]
Beer_Data_Exo = Beer_Data[, c('cos.weeks', 'sin.weeks', 'B1_lnDist', 'B3_lnDist',
                        'B1_lnFeat', 'B3_lnFeat', 'B1_lnDisp', 'B3_lnDisp',
                        'B1_lnFeatDisp', 'B3_lnFeatDisp')]




#The trend does not have to be added here, as it can be immediately added through type "both"
```

```
VARselect(Beer_Data_Endo,lag.max = 4, type = "both", exogen = Beer_Data_Exo)
#SC says 1 lag which is the BIC so use 1 lag!!!

# Symmetry or asymmetry? Probably symmetry as asymmetry is too difficult
# (Include the evolving series in first differences)
# Include the stationary series in levels
# All stationary so all in levels


#Estimating the VAR model, and reporting results for the individual 6 equations
Beer_Data_Est <- VAR(Beer_Data_Endo, p=1, type = "both", exogen = Beer_Data_Exo)

#immediate effect is the covariance matrix with its divisions! Not possible to
#say something about the significance!

summary(Beer_Data_Est, "B1_lnSal")
summary(Beer_Data_Est,"B3_lnSal")
summary(Beer_Data_Est,"B1_lnAdv")
summary(Beer_Data_Est,"B3_lnAdv")
summary(Beer_Data_Est,"B1_lnPrice")
summary(Beer_Data_Est,"B3_lnPrice")



#Generating the IRFs!!!
#n.ahead = 13!!!! -> 1 Quarter of the year
#cumulative  IRF results is the dynamic effect!

#Generating the IRFs B1

#IRF B1 Sales - No significant results
Beer_IRF1 <- irf(Beer_Data_Est, impulse = NULL, response = "B1_lnSal", n.ahead = 13,
            ortho = TRUE, cumulative = FALSE, boot = TRUE, ci = 0.90,
            runs = 500)
plot(Beer_IRF1)

Beer_IRF2 <- irf(Beer_Data_Est, impulse = NULL, response = "B1_lnSal", n.ahead = 13,
            ortho = TRUE, cumulative = TRUE, boot = TRUE, ci = 0.90,
            runs = 500)
plot(Beer_IRF2)

#IRF B1 Advertising - A shock in sales of B1 increases advertising (cumulatively) - goes to around 0.45 after 5 weeks
Beer_IRF3 <- irf(Beer_Data_Est, impulse = NULL, response = "B1_lnAdv", n.ahead = 13,
            ortho = TRUE, cumulative = FALSE, boot = TRUE, ci = 0.90,
```

```
        runs = 500)
plot(Beer_IRF3)


Beer_IRF4 <- irf(Beer_Data_Est, impulse = NULL, response = "B1_lnAdv", n.ahead = 13,
        ortho = TRUE, cumulative = TRUE, boot = TRUE, ci = 0.90,
        runs = 500)
plot(Beer_IRF4)


#IRF B1 Price - No significant results
Beer_IRF5 <- irf(Beer_Data_Est, impulse = NULL, response = "B1_lnPrice", n.ahead = 13,
        ortho = TRUE, cumulative = FALSE, boot = TRUE, ci = 0.90,
        runs = 500)
plot(Beer_IRF5)


Beer_IRF6 <- irf(Beer_Data_Est, impulse = NULL, response = "B1_lnPrice", n.ahead = 13,
        ortho = TRUE, cumulative = TRUE, boot = TRUE, ci = 0.90,
        runs = 500)
plot(Beer_IRF6)

#Generating IRFs B3 - A shock in sales of B1 increases sales of B3 (goes to around .10), a shock in sales of B1 increases sales of B3 (cumulatively) - goes to around 0.17 after 8 weeks

#IRF B3 Sales
Beer_IRF7 <- irf(Beer_Data_Est, impulse = NULL, response = "B3_lnSal", n.ahead = 13,
        ortho = TRUE, cumulative = FALSE, boot = TRUE, ci = 0.90,
        runs = 500)
plot(Beer_IRF7)


Beer_IRF8 <- irf(Beer_Data_Est, impulse = NULL, response = "B3_lnSal", n.ahead = 13,
        ortho = TRUE, cumulative = TRUE, boot = TRUE, ci = 0.90,
        runs = 500)
plot(Beer_IRF8)

#IRF B3 Advertising - A shock in sales of B3 increases advertising of B3 (to 0.2 (week 1) and 0.4 (week 2)), an increase in sales of B3 increases advertising of B3 (cumulatively) - to around 0.7 after 4 weeks
Beer_IRF9 <- irf(Beer_Data_Est, impulse = NULL, response = "B3_lnAdv", n.ahead = 13,
        ortho = TRUE, cumulative = FALSE, boot = TRUE, ci = 0.90,
        runs = 500)
plot(Beer_IRF9)

Beer_IRF10 <- irf(Beer_Data_Est, impulse = NULL, response = "B3_lnAdv", n.ahead = 13,
```

```
            ortho = TRUE, cumulative = TRUE, boot = TRUE, ci = 0.90,
            runs = 500)
plot(Beer_IRF10)

#IRF B3 Price - A shock in sales of B3 decreases price of B3 to -0.0035 (week 1). A shock in sales of brand 3 decreases price of brand 3 to around -0.0045 after 8 weeks (cumulatively). A shock in price of B1 increases price of B3 to around 0.055 after 12 weeks (cumulatively).
Beer_IRF11 <- irf(Beer_Data_Est, impulse = NULL, response = "B3_lnPrice", n.ahead = 13,
            ortho = TRUE, cumulative = FALSE, boot = TRUE, ci = 0.90,
            runs = 500)
plot(Beer_IRF11)


Beer_IRF12 <- irf(Beer_Data_Est, impulse = NULL, response = "B3_lnPrice", n.ahead = 13,
            ortho = TRUE, cumulative = TRUE, boot = TRUE, ci = 0.90,
            runs = 500)
plot(Beer_IRF12)


###Generating the FEVDs
#FEVDs with pre-specified causal ordering required
Beer_FEVD1 <-fevd(Beer_Data_Est,n.ahead = 13)
Beer_FEVD1
barbasis1 = Beer_FEVD1[1]
barbasis2 = as.matrix(unlist(barbasis1),ncol =6, byrow = TRUE)

#Only select weeks of intervals of 13
bartry = Reduce(rbind,Beer_FEVD1)
bartry2 = t(bartry)
bartry2 = bartry2[,c(13, 26, 39, 52, 65, 78)]

#Plot graphics
library(gplots)
library(RColorBrewer)
library(grDevices)

#FEVD plot
barplot(bartry2, col = c("red", "black", "white", "blue", "green", "yellow"), xlab = "FEVD Brand 1 and 3", ylab = "Sales, Advertising, Price", names.arg = c("Sales B1", "Sales B3", "Advertising B1", "Advertising B3", "Price B1", "Price B3"))
legend("topright", legend = c("Sales B1", "Sales B3", "Advertising B1", "Advertising B3", "Price B1", "Price B3"), fill = c("red", "black", "white", "blue", "green", "yellow"))
```