Buy Online Pickup In Store

Bharati Malik

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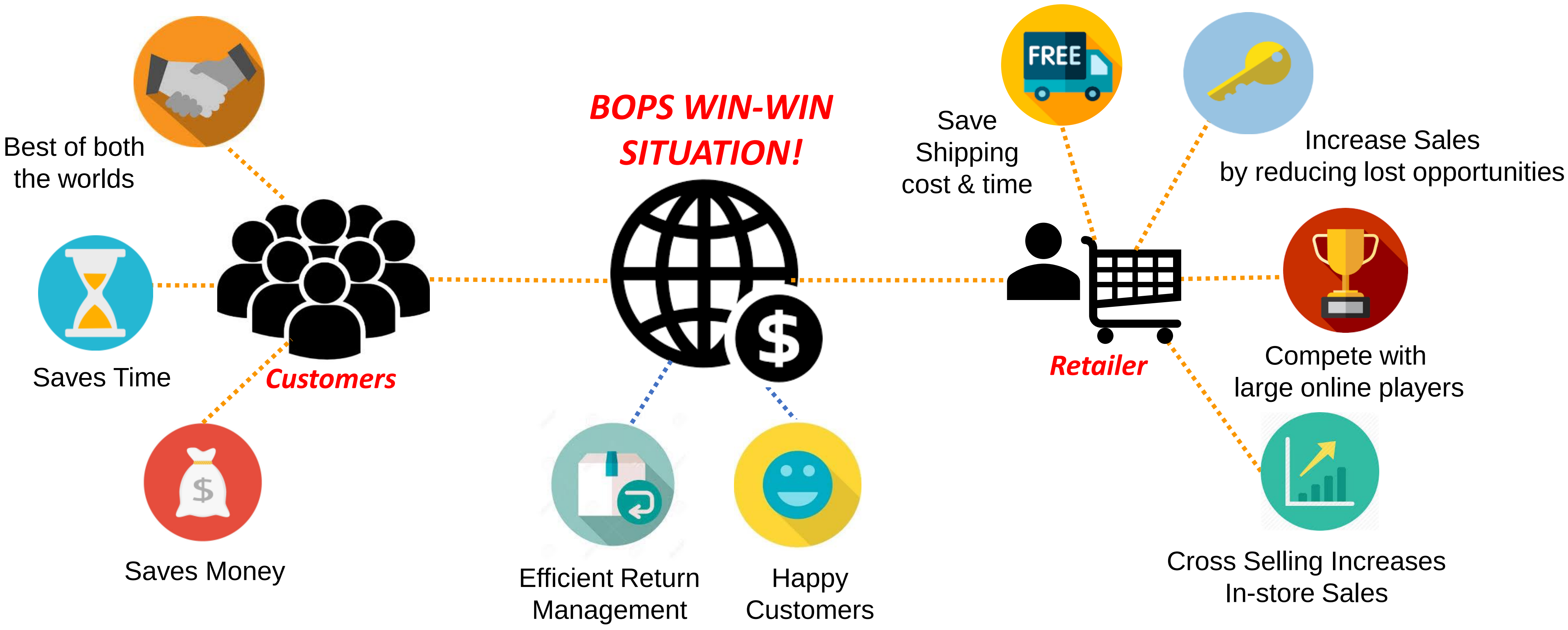
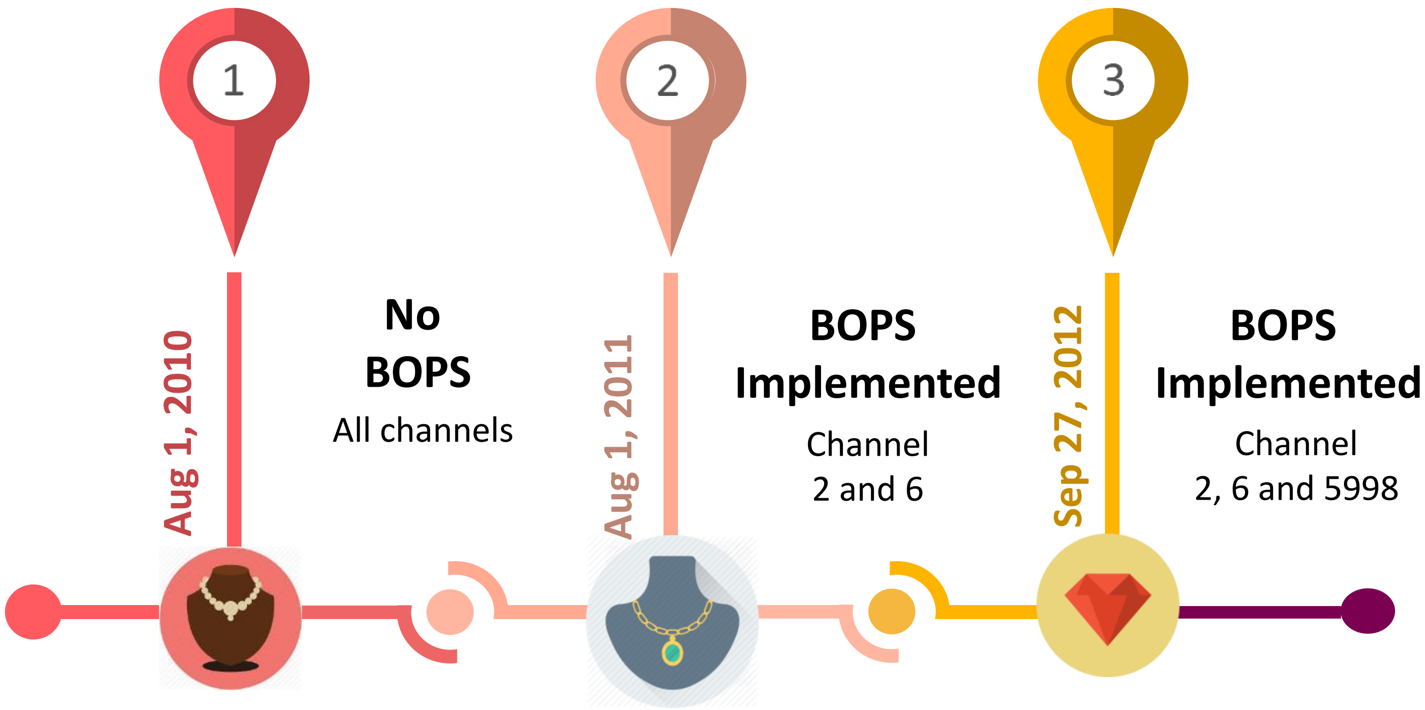
Business Context: Why Buy Online Pickup In Store?



Business Context: BOPS Application for a Jewelry Brand

- Online jewelry transactions between August 1st, 2010 and July 31st, 2013.
- Implementation of BOPS on three online channels with store number 2, 6 and 5998.

BOPS IMPLEMENTATION TIMELINE



Research Question

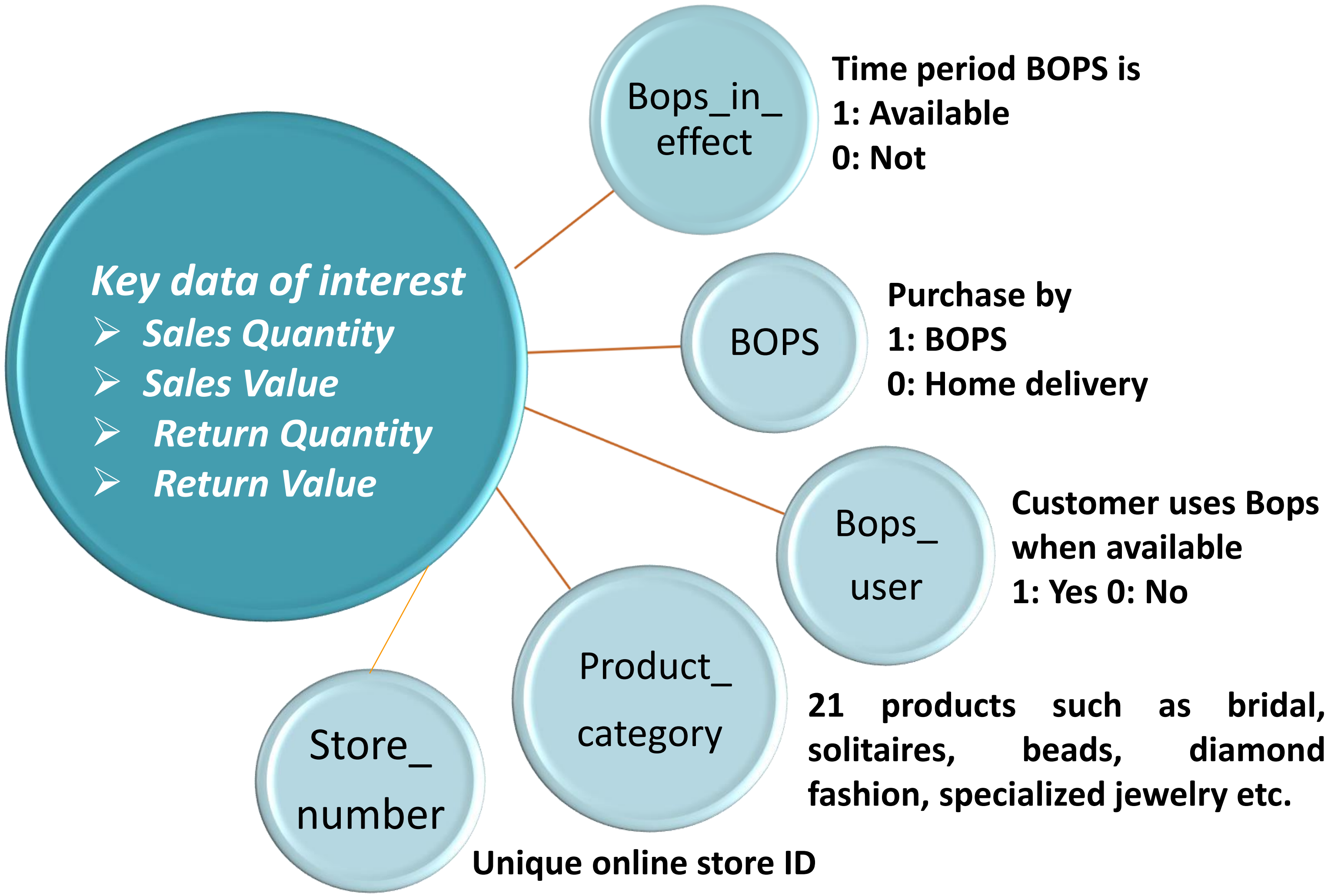
What is the impact of implementing *BOPS* on

Overall online channel sales and return ?

Online customer purchase and return behavior?

Product level sales and returns ?

Data Overview



Analysis: Overall Channel Sales

Impact on Sales after BOPS Implementation		
	Sales (in $ value)	*Sales (in quantity)*
Overall Impact	49.4% Decrease	33.3% Decrease
Product Level Impact	28.8 % Decrease	31.66% Decrease

Overall sales value and quantity depicted counter intuitive* results with a decrease!

Likely reason: Knowledge of availability of product (jewelry - highly priced!) in store location increases the inclination to see, trust and then buy products at that physical store, leading to increased physical store sales and decreased online sales.

Product level sales decrease is comparatively less and depicting a clearer picture!

Likely reason: Product category is explaining the variation in sales value and return value even better due to more sample observations.

Analysis: Impact on Sales Value – Product Level

Basis the level of impact, we grouped these together in three broader categories – No Impact, Low Impact and High Impact.

No Impact(~0%)

Categories

Mens

Gold Earrings

Insight

Indicates that there is a low demand for these categories

Positive Impact

Categories

Beads

Watches

Insight

Indicates that no trials required for these products categories

Negative Low Impact

Categories-Low (<30%)

Solitaires, Semi-Precious, Diamond Solitaires Jewellery, Diamond Wedding Bands

Insight

Indicates that these are high priced categories when customers check the inventory status online and prefer to buy it in store.

Negative High Impact

Categories-High(>30%)

Bridal, Gold Wed Bands, Diamond Fashion, Gold Chain Jewellery, Pre-owned, Sterling Silver

Insight

Indicates that these might be low priced categories where product quality is not the priority and prefer home deliveries.

Analysis: Overall Channel Returns

Impact on Returns after BOPS Implementation		
	Return (in $ value)	*Return (in quantity)*
Overall Impact	66.0% Decrease	17.2% Decrease
Product Level Impact	33.3% Decrease	38.5% Decrease

Overall return quantity and value depicted a decrease, good for us!

Likely reason: Inventory information leading customers to visit their nearest store and then ordering online*, after ensuring satisfaction about value and durability --> leading to less returns.

Product level returns, comparatively showing less decrease.

Likely reason: Product category is explaining the variation in return even better due to more sample observations.

Analysis: Impact on Return Value – Product Level

Basis the level of impact, we grouped these together in three broader categories – No Impact, Low Impact and High Impact.

No Impact(~0%)

Categories:
Semi Precious
Men’s
Gold Earrings

Insight:
There is low demand and low sales, so low returns

Positive High Impact

Categories:
Solitaires,
Diamond Fashion,
Watches,
Diamond Wedding Bands,
Sterling Silver

Insight:
Requires quality satisfaction check before purchase.

Positive Low Impact

Categories:
Bridal,
Gold Wed Bands,
Gold Chain,
Bridal,
Beads,
Pre-owned

Insight: Indicates that sales value is less

Negative Impact

Categories
Gold Wed Bands,
Diamond Solitaire Jewellery

Insight: Indicates these products are not meeting customer expectations.

Analysis: Customer level analysis – Buying and Return Behavior

Buying Behavior

Impact on Sales of using BOPS Service		
	Sales Quantity	*Sales Value*
Bops User	4.1% Decrease	4.4% Decrease

- A customer using BOPS service buys **4.1%** less quantity and **4.4 %** less sales value than a customer who doesn't use BOPS service.
- It is likely that a customer using BOPS has easy access to the store and might prefer to do most of the purchases in-store, given that the inventory information is now available.

Return Behavior

- Return propensity of a customer who uses BOPS service is ***36.9 PERCENTAGE POINTS*** more than a customer who doesn't use BOPS Service.
- Ease of return that comes with using BOPS service is a likely explanation of the higher probability of return behavior. If the product doesn't match consumer's expectation, they can initiate a return easily since they are already at store.

Insights and Recommendations

Currently, overall online sales is showing a decreasing trend after BOPS strategy implementation. Over a period:

- Understand the ***CHANNEL SHIFT EFFECT***, shift of customers from the online to the brick-and-mortar channel and the conversion of online customers to store customers.
- Measure the true impact of BOPS by analyzing ***ONLINE AND PHYSICAL STORE SALES*** together.
- Focus on products with positive impact on sales and less returns : ***BEADS and WATCHES.***

- Increase in return probability for online purchases: To reduce returns, ***ENHANCE BOPS EXPERIENCE.***

  ✓ Train in-store employees for a seamless BOPS execution; better customer experience.
  ✓ Dedicated counters for BOPS pick-ups and related customer enquiries.
  ✓ Online inventory should be in sync with in-store availability.
  ✓ Satisfied customer testimonials on website (i.e. product quality, accept refunds and store pick up is hassle free).

Limitations

- ***DISTANCE*** between customer’s residence and nearest pick-up store location.

- More information required on ***STORE CHANNELS***, currently limited to store number 2, 6 and 5998.

- Information required for ***SHIPPING POLICY.***

- No information about physical store sales and returns for measuring BOPS true impact (***CROSS-SELLING*** effect due to sales of additional products).

Appendix

Model – Question 1

salesquantity = $\beta 0 + \beta 1(\text{BIE\_timeline} * \text{group\_store}) + \beta 2\text{month\_dummy} + \beta 3\text{avg\_female} + \beta 4\text{avg\_age} + \beta 5\text{avg\_income} + \beta 6\text{avg\_homeowner} + \beta 7\text{avg\_childowner}$

log(salesvalue)= $\beta 0 + \beta 1(\text{BIE\_timeline} * \text{group\_store}) + \beta 2\text{month\_dummy} + \beta 3\text{avg\_female} + \beta 4\text{avg\_age} + \beta 5\text{avg\_income} + \beta 6\text{avg\_homeowner} + \beta 7\text{avg\_childowner}$

Model – Question 2

returnquantity = $\beta 0 + \beta 1(\text{BIE\_timeline} * \text{group\_store}) + \beta 2\text{month\_dummy} + \beta 3\text{avg\_female} + \beta 4\text{avg\_age} + \beta 5\text{avg\_income} + \beta 6 \text{ log\_salesquantity}$

log(returnvalue)= = $\beta 0 + \beta 1(\text{BIE\_timeline} * \text{group\_store}) + \beta 2\text{month\_dummy} + \beta 3\text{avg\_female} + \beta 4\text{avg\_age} + \beta 5\text{avg\_income} + \beta 6 \text{ log\_salesvalue}$

Model – Question 3

salesquantity = $\beta 0 + \beta 1(\text{bops\_in\_effect} * \text{BOPS\_user} + \beta 2\text{purchase\_time\_period} + \beta 3\text{store\_number} + \beta 4\text{age\_band} + \beta 5\text{est\_income\_code} + \beta 6\text{homeowner} + \beta 7\text{child}$

log(salesvalue) = $\beta 0 + \beta 1(\text{bops\_in\_effect} * \text{BOPS\_user} + \beta 2\text{purchase\_time\_period} + \beta 3\text{store\_number} + \beta 4\text{age\_band} + \beta 5\text{est\_income\_code} + \beta 6\text{homeowner} + \beta 7\text{child}$

Model – Question 4

Initial Model:

Return = $\beta0+\beta1$ bops+ $\beta2$ logprice + $\beta3$ product_category+ $\beta4$ store_number+ $\beta5$ month_dummy + $\beta6$ year+ $\beta7$ est_income_code + $\beta8$ female + $\beta9$ age_band

Final Model:

Stage 1:

bops = $\Upsilon0$ + $\Upsilon1$ length_of_residence + $\Upsilon2$ child + $\Upsilon3$ logprice + $\Upsilon4$ product_category+ $\Upsilon5$store_number+ $\Upsilon6$ month_dummy + $\Upsilon7$ year+ $\Upsilon8$ est_income_code + $\Upsilon9$ female + $\Upsilon10$ age_band

Stage 2:

Return = $\beta0+\beta1$ bops*+ $\beta2$ logprice + $\beta3$ product_category+ $\beta4$ store_number+ $\beta5$ month_dummy + $\beta6$ year+ $\beta7$ est_income_code + $\beta8$ female + $\beta9$ age_band

Model – Question 5

salesquantity = $\beta 0 + \beta 1(\text{BIE\_timeline} * \text{group\_store}) + \beta 2\text{month\_dummy} + \beta 3\text{avg\_female} + \beta 4\text{avg\_age} + \beta 5\text{avg\_income} +$ $\beta 6$avg_homeowner+ $\beta 7$avg_childowner + $\beta 8$ product_category

log(salesvalue)= $\beta 0 + \beta 1(\text{BIE\_timeline} * \text{group\_store}) + \beta 2\text{month\_dummy} + \beta 3\text{avg\_female} + \beta 4\text{avg\_age} + \beta 5\text{avg\_income} +$ $\beta 6$avg_homeowner + $\beta 8$ product_category

returnquantity = $\beta 0 + \beta 1(\text{BIE\_timeline} * \text{group\_store}) + \beta 2\text{month\_dummy} + \beta 3\text{avg\_female} + \beta 4\text{avg\_age} + \beta 5\text{avg\_income} +$ $\beta 6$ log_salesquantity + $\beta 8$ product_category

log(returnvalue)= = $\beta 0 + \beta 1(\text{BIE\_timeline} * \text{group\_store}) + \beta 2\text{month\_dummy} + \beta 3\text{avg\_female} + \beta 4\text{avg\_age} +$ $\beta 5\text{avg\_income} + \beta 6$ log_salesvalue + $\beta 8$ product_category

Model – Question 6

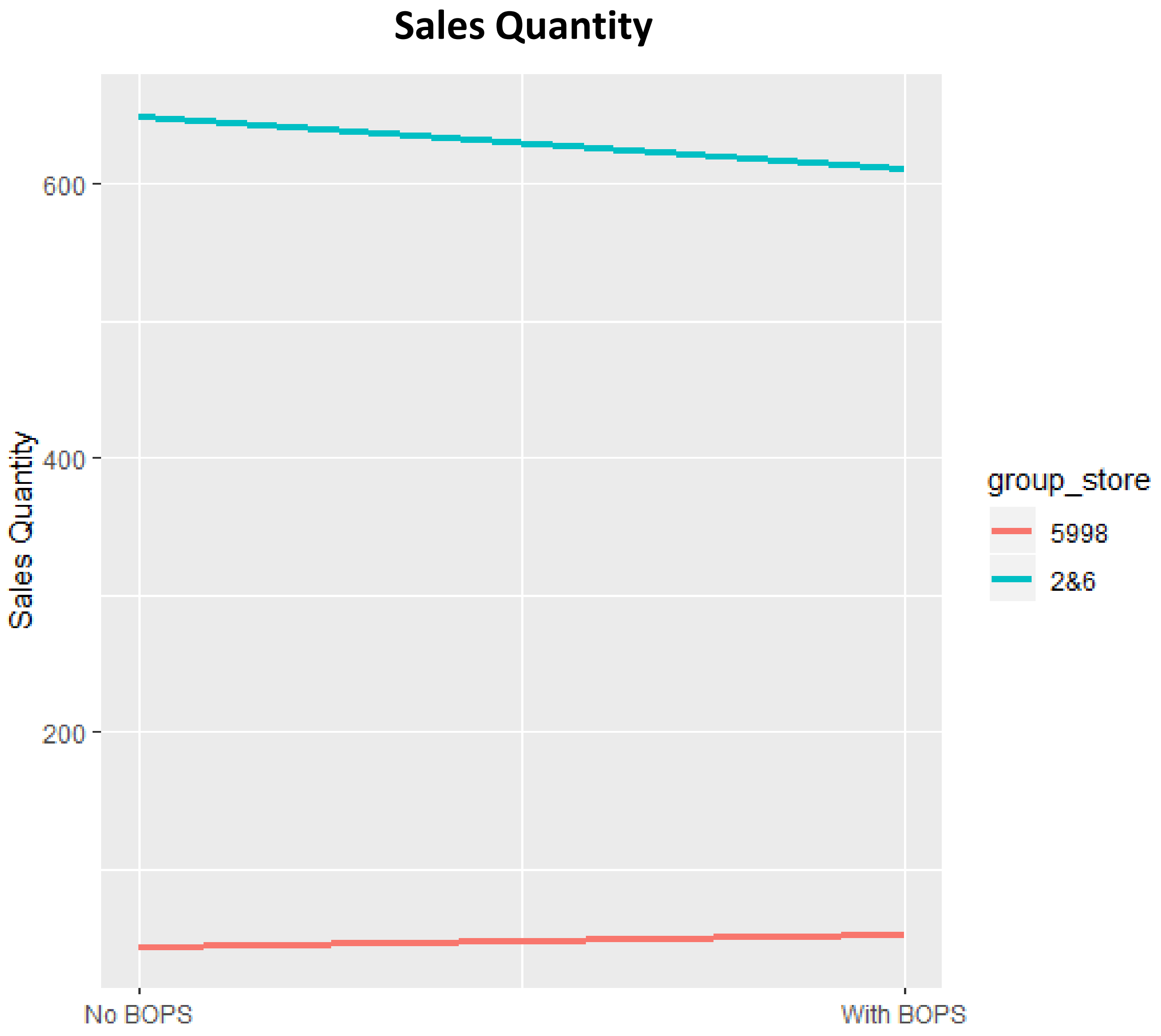
log(salesvalue)= $\beta 0 + \beta 1(\text{BIE\_timeline} * \text{group\_store} * \text{product\_category}) + \beta 2\text{month\_dummy} + \beta 3\text{avg\_female} +$ $\beta 4\text{avg_age} + \beta 5\text{avg_income} + \beta 6$avg_homeowner+ $\beta 7$avg_childowner

log(returnvalue)= = $\beta 0 + \beta 1(\text{BIE\_timeline} * \text{group\_store} * \text{product\_category}) + \beta 2\text{month\_dummy} + \beta 3\text{avg\_female} +$ $\beta 4\text{avg\_age} + \beta 5\text{avg\_income} + \beta 6$ log_salesvalue

Impact of BOPS on Online Sales Quantity

as.factor(month_dummy)11	1.444**	1.444**
	(0.139)	(0.132)
as.factor(month_dummy)12	3.249***	3.249***
	(0.139)	(0.126)
avg_female	0.304***	0.304***
	(0.178)	(0.182)
avg_age	0.838***	0.838***
	(0.020)	(0.021)
avg_income	1.323***	1.323***
	(0.037)	(0.037)
avg_homeowner	0.486***	0.486***
	(0.188)	(0.184)
avg_childowner	0.896	0.896
	(0.201)	(0.228)
BIE_timeline:group_store	0.667**	0.667**
	(0.133)	(0.114)
Constant	59.310***	59.310***
	(0.268)	(0.256)
Observations	2,005	2,005
Log Likelihood	-13,277.700	-13,277.700
theta	0.636*** (0.017)	0.636*** (0.017)
Akaike Inf. Crit.	26,595.410	26,595.410
Note:		*p<0.05; **p<0.01; ***p<0.001

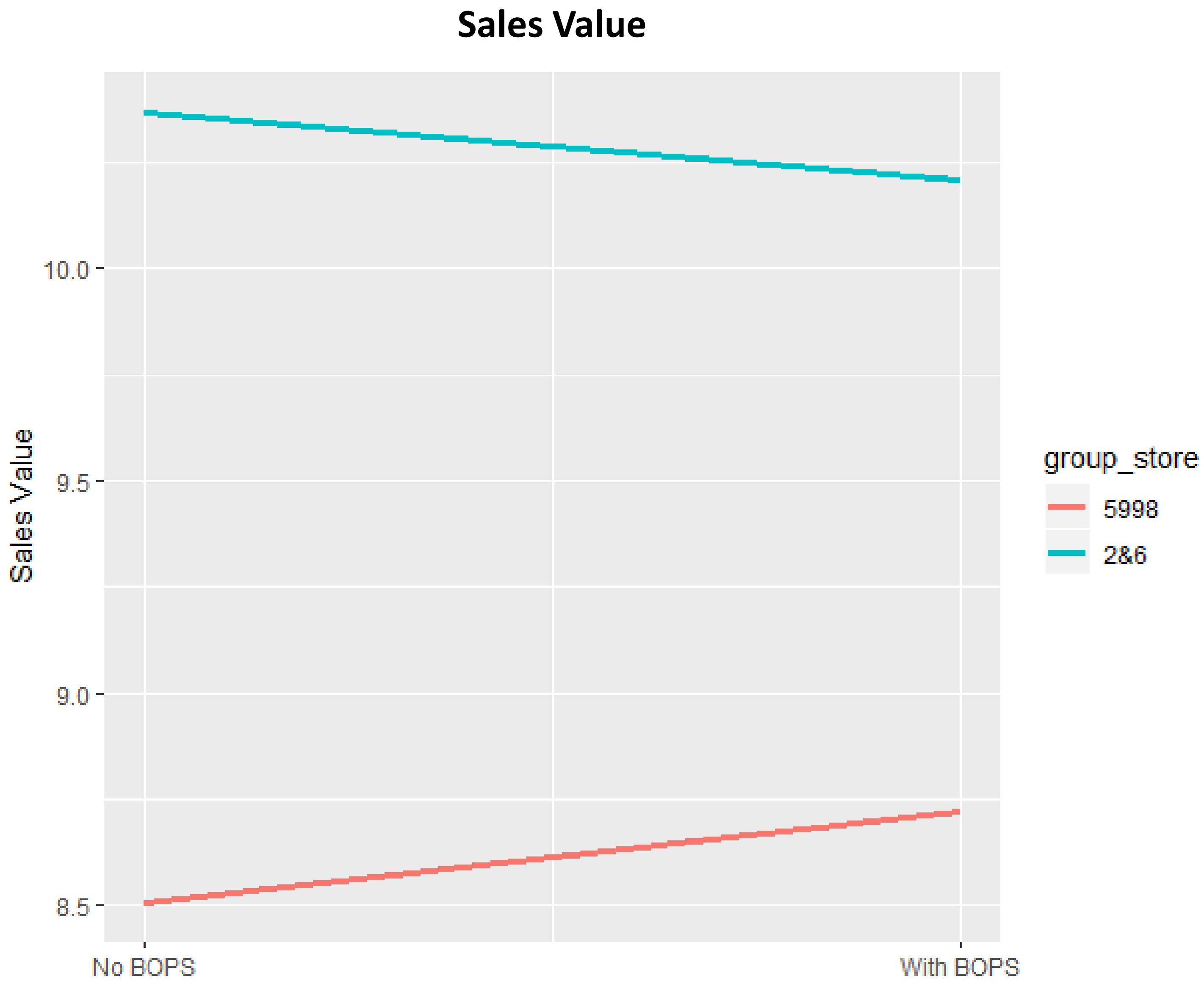
```
> # Check for heteroscedasticity
> gqtest(negbin11) # Goldfeld-Quandt test indicates no heteroscedasticity

        Goldfeld-Quandt test

data:  negbin11
GQ = 0.0040545, df1 = 983, df2 = 982, p-value = 1
alternative hypothesis: variance increases from segment 1 to 2

> bptest(negbin11) # Breusch-Pagan test indicates heteroscedasticity

        studentized Breusch-Pagan test

data:  negbin11
BP = 350.98, df = 19, p-value < 2.2e-16
```



Impact of BOPS on Online Sales Value

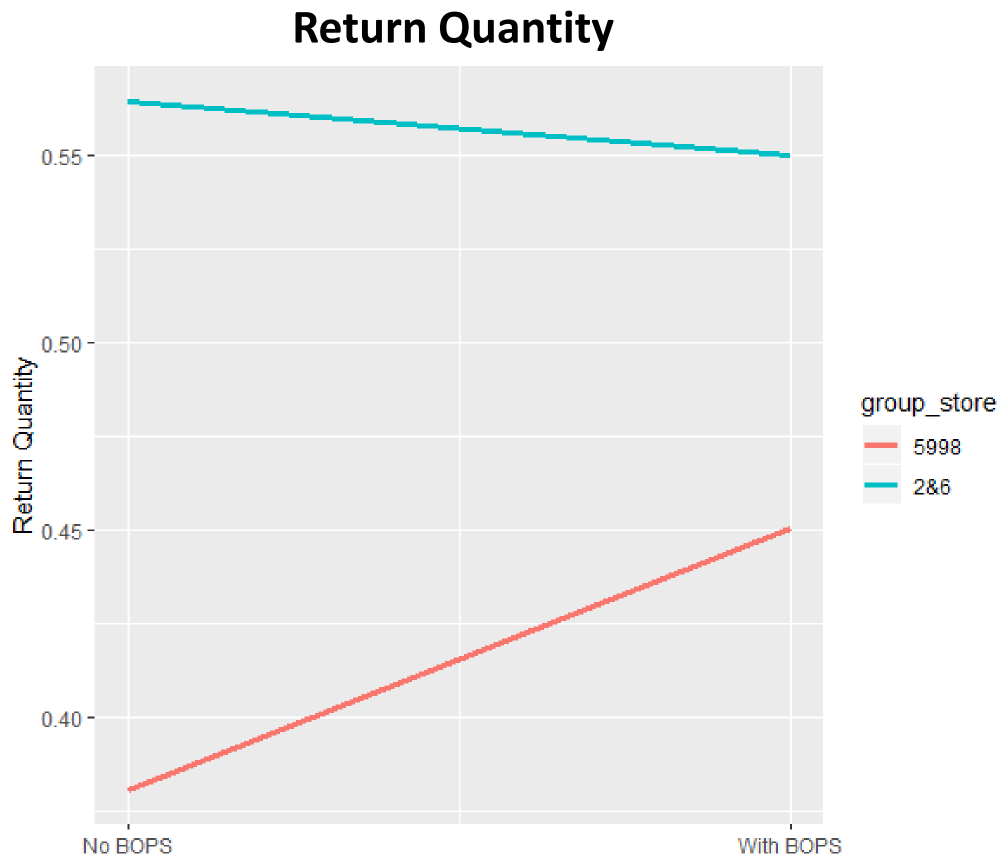
	(0.226)	(0.239)
as.factor(month_dummy)11	0.453*	0.453
	(0.217)	(0.239)
as.factor(month_dummy)12	1.451***	1.451***
	(0.218)	(0.225)
avg_female	-1.128***	-1.128*
	(0.278)	(0.478)
avg_age	-0.192***	-0.192***
	(0.031)	(0.047)
avg_income	0.283***	0.283**
	(0.058)	(0.100)
avg_homeowner	-0.544	-0.544
	(0.295)	(0.490)
avg_childowner	0.764*	0.764
	(0.314)	(0.605)
BIE_timeline:group_store	-0.494*	-0.494**
	(0.207)	(0.168)
Constant	8.366***	8.366***
	(0.418)	(0.664)
Observations	2,005	2,005
R2	0.178	0.178
Adjusted R2	0.170	0.170
Residual Std. Error	1.969	1.969
F Statistic	22.580***	22.580***
Note:		*p<0.05; **p<0.01; ***p<0.001

```
> # Check for heteroscedasticity
> gqtest(ols11) # Goldfeld-Quandt test indicates no heteroscedasticity

        Goldfeld-Quandt test

data:  ols11
GQ = 0.61023, df1 = 983, df2 = 982, p-value = 1
alternative hypothesis: variance increases from segment 1 to 2

> bptest(ols11) # Breusch-Pagan test indicates heteroscedasticity

        studentized Breusch-Pagan test

data:  ols11
BP = 72.346, df = 19, p-value = 0.00000003732
```



Impact of BOPS on Online Return Quantity

```
                            (0.043)          (0.041)

as.factor(month_dummy)9     0.716***         0.716***
                            (0.044)          (0.040)

as.factor(month_dummy)10    0.807***         0.807***
                            (0.047)          (0.040)

as.factor(month_dummy)11    0.744***         0.744***
                            (0.044)          (0.037)

as.factor(month_dummy)12    0.691***         0.691***
                            (0.043)          (0.042)

avg_age                     0.967***         0.967***
                            (0.010)          (0.010)

avg_income                   0.987            0.987
                            (0.017)          (0.017)

avg_childowner               1.134            1.134
                            (0.099)          (0.096)

BIE_timeline:group_store     0.825**          0.825**
                            (0.060)          (0.066)

Constant                    0.118***         0.118***
                            (0.118)          (0.124)

-------------------------------------------------------------
Observations                 2,005            2,005
Log Likelihood            -6,344.996       -6,344.996
theta                  11.822*** (0.645) 11.822*** (0.645)
Akaike Inf. Crit.          12,727.990       12,727.990
=============================================================
Note:                        *p<0.05; **p<0.01; ***p<0.001
```



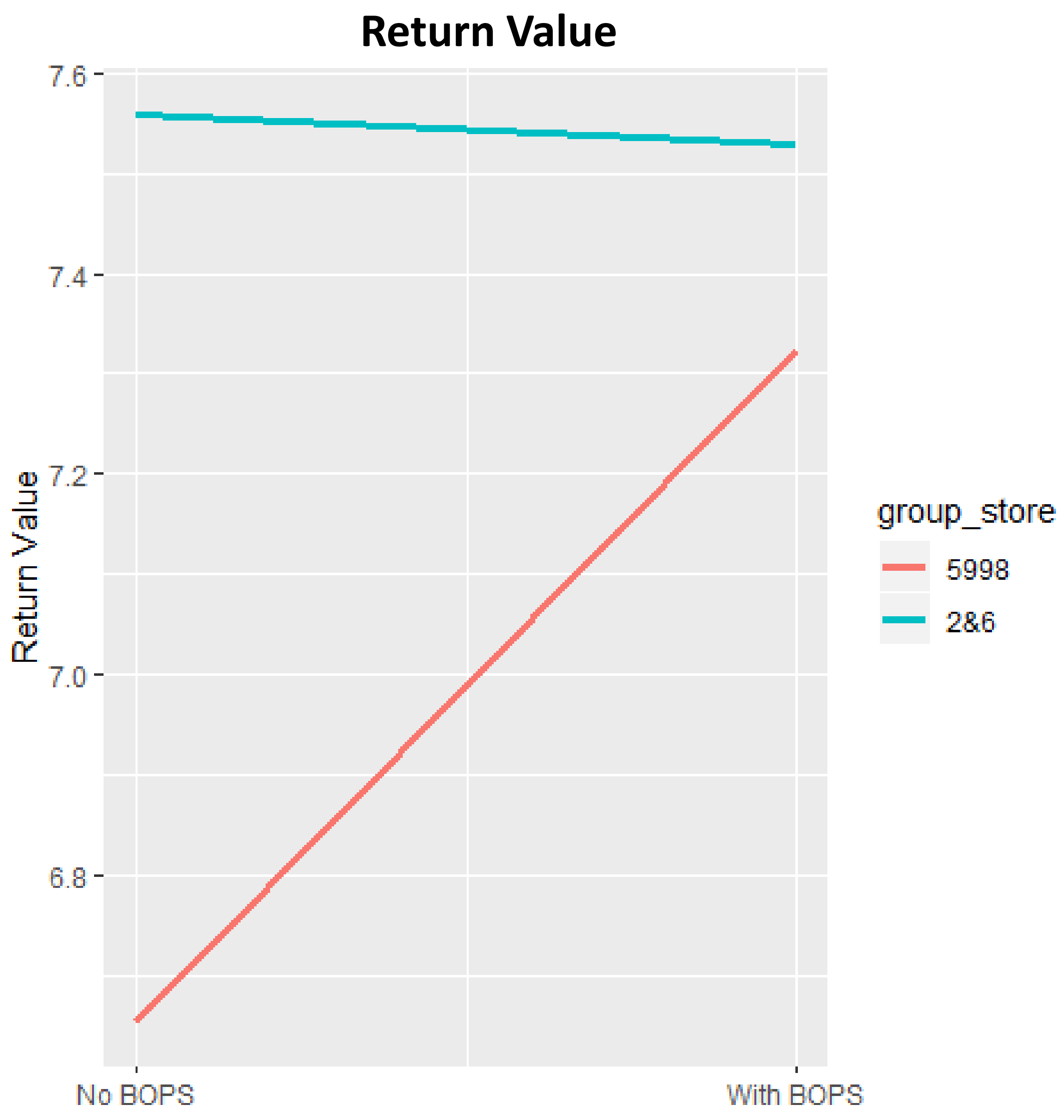

```
Likelihood ratio test

Model 1: returnquantity ~ BIE_timeline * group_store + log(salesquantity) +
    avg_age + avg_income + avg_childowner
Model 2: salesquantity ~ 1
  #Df    LogLik Df Chisq Pr(>Chisq)
1   9   -6418.1
2   2 -13856.2 -7 14876  < 2.2e-16 ***
---
Signif. codes:  0 ‘***’ 0.001 ‘**’ 0.01 ‘*’ 0.05 ‘.’ 0.1 ‘ ’ 1
```

```
> # Check for heteroscedasticity
> gqtest(negbin21) # Goldfeld-Quandt test indicates no heteroscedasticity

        Goldfeld-Quandt test

data:  negbin21
GQ = 0.005134, df1 = 984, df2 = 983, p-value = 1
alternative hypothesis: variance increases from segment 1 to 2

> bptest(negbin21) # Breusch-Pagan test indicates heteroscedasticity

        studentized Breusch-Pagan test

data:  negbin21
BP = 158.63, df = 18, p-value < 2.2e-16
```

Impact of BOPS on Online Return Value

	(0.158)	(0.173)
as.factor(month_dummy)8	-0.588***	-0.588***
	(0.148)	(0.145)
as.factor(month_dummy)9	-0.355*	-0.355*
	(0.153)	(0.142)
as.factor(month_dummy)10	-0.511**	-0.511**
	(0.164)	(0.161)
as.factor(month_dummy)11	-0.593***	-0.593***
	(0.158)	(0.157)
as.factor(month_dummy)12	-0.683***	-0.683***
	(0.159)	(0.135)
avg_age	-0.020	-0.020
	(0.022)	(0.031)
avg_income	0.034	0.034
	(0.041)	(0.061)
avg_childowner	0.377	0.377
	(0.220)	(0.303)
BIE_timeline:group_store	-0.677***	-0.677***
	(0.150)	(0.199)
Constant	-5.229***	-5.229***
	(0.307)	(0.436)
Observations	2,005	2,005
R2	0.789	0.789
Adjusted R2	0.787	0.787
Residual Std. Error	1.429	1.429
F Statistic	412.043***	412.043***

```
> # Check for heteroscedasticity
> gqtest(ols21) # Goldfeld-Quandt test indicates no heteroscedasticity

        Goldfeld-Quandt test

data:  ols21
GQ = 2.2513, df1 = 984, df2 = 983, p-value < 2.2e-16
alternative hypothesis: variance increases from segment 1 to 2

> bptest(ols21) # Breusch-Pagan test indicates heteroscedasticity

        studentized Breusch-Pagan test

data:  ols21
BP = 427.29, df = 18, p-value < 2.2e-16
```



Customer level analysis – Purchase Behavior

Negative Binomial Results

	Dependent variable:	
	salesquantity	
	Normal SE (1)	HW-Robust SE (2)
bops_in_effect	0.811*** (0.007)	0.811*** (0.022)
bops_user	1.031** (0.011)	1.031** (0.023)
purchase_time_period	1.125*** (0.001)	1.125*** (0.002)
est_income_code	1.013*** (0.001)	1.013*** (0.004)
age_band	0.999 (0.001)	0.999 (0.002)
factor(store_number)6	1.024* (0.012)	1.024* (0.014)
factor(store_number)5998	0.753 (0.180)	0.753 (0.122)
homeowner_coden	0.996 (0.007)	0.996 (0.022)
childn	1.002 (0.006)	1.002 (0.012)
bops_in_effect:bops_user	0.959** (0.015)	0.959** (0.031)

```
Likelihood ratio test

Model 1: salesquantity ~ bops_in_effect * bops_user + purchase_time_period +
    est_income_code + age_band + factor(store_number) + homeowner_coden +
    childn
Model 2: salesquantity ~ 1
  #Df  LogLik  Df Chisq Pr(>Chisq)
1  12 -149140
2   2 -167228 -10 36177  < 2.2e-16 ***
---
Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
```

```
> bptest(negbin32) # Breusch-Pagan test indicates heteroskedasticity

        studentized Breusch-Pagan test

data:  negbin32
BP = 34.768, df = 10, p-value = 0.0001368
```

Regression Results

	Dependent variable:	
	log_salesvalue	
	Normal SE (1)	HW-Robust SE (2)
bops_in_effect	-0.144*** (0.008)	-0.144*** (0.022)
bops_user	-0.222*** (0.012)	-0.222*** (0.023)
purchase_time_period	0.106*** (0.001)	0.106*** (0.002)
est_income_code	0.008*** (0.002)	0.008* (0.004)
age_band	0.005*** (0.001)	0.005* (0.002)
factor(store_number)6	-0.098*** (0.014)	-0.098*** (0.014)
factor(store_number)5998	0.341 (0.181)	0.341** (0.122)
homeowner_coden	-0.004 (0.008)	-0.004 (0.022)
childn	-0.045*** (0.007)	-0.045*** (0.012)
bops_in_effect:bops_user	-0.044* (0.018)	-0.044 (0.031)

Customer level analysis – Return Behavior

Logit Model Highlights

Return Prediction

Classified based on return	*True Value*		*Total*
	0	1	
0	887590	33	887623
1	99465	11	99476
Total	987055	44	987099

```
> table(trans_level2$return, pred42>=0.5)

     FALSE   TRUE
  0 887590     33
  1  99465     11
```

Correct classification rate = $\frac{887590+11}{987099} = 89.92\%$

```
> print(paste('Accuracy',1-misClasificError42))
[1] "Accuracy 0.89920159983953"
```

Return: Logit Ratio

Return	*Count*	*Number of independent variable*	*Ratio*	*Satisfies the 10:1 requirement*
1 (Yes)	99476	21	99476/21	Yes
0 (No)	887623	21	887623/21	Yes

```
Likelihood ratio test

Model 1: return ~ bops + logprice + product_category + f_store + f_month +
    f_year + est_income_code + female + age_band
Model 2: return ~ 1
  #Df  LogLik  Df Chisq Pr(>Chisq)
1  22 -309446
2   1 -322569 -21 26246  < 2.2e-16 ***
---
Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
```

Customer level analysis – Return Behavior

Since using BOPS is a customer's decision, we suspect that key independent variable is **Endogenous**

Omitted Variable: Proximity
Endogenous Variable: BOPS

Instrument Variables:
1. Length of Residence
2. Child

OLS Regression Results

	Dependent variable: return	
	Normal SE (1)	HW-Robust SE (2)
bops	0.0151*** (0.0007)	0.0151*** (0.0007)
logprice	0.0354*** (0.0002)	0.0354*** (0.0002)
product_category	-0.0007*** (0.00005)	-0.0007*** (0.00005)
f_store6	-0.0063*** (0.0012)	-0.0063*** (0.0011)

Logit Results

	Dependent variable: return	
	Marginal Effects (1)	Marg.Eff.w/RobStdEr (2)
bops	0.01603*** (0.00070)	0.01603*** (0.00070)
logprice	0.03755*** (0.00025)	0.03755*** (0.00024)
product_category	-0.00011* (0.00004)	-0.00011* (0.00004)
f_store6	-0.00598*** (0.00110)	-0.00598*** (0.00109)

```
> confint(lpm41,"bops") # (
           2.5 %      97.5 %
bops 0.01369205 0.01651074
```

```
No variable from the 8 input variables has collinearity problem.

The linear correlation coefficients ranges between:
min correlation ( age_band ~ product_category ):  -0.001363695
max correlation ( year ~ month_dummy ):  -0.6462742

---------- VIFs of the remained variables --------
         Variables      VIF
1             bops 1.019906
2      month_dummy 1.734829
3 product_category 1.012478
4           female 1.045504
5         logprice 1.039249
6             year 1.747685
7         age_band 1.036748
8  est_income_code 1.025771
```

*Results of OLS model and Logit models are comparable

Customer level analysis – Return Behavior

2SLS model to treat **Endogeneity**

```
ivreg(formula = return ~ bops + logprice + product_category +
    f_store + f_month + f_year + est_income_code + female + age_band |
    length_of_residence + child + logprice + product_category +
        f_store + f_month + f_year + est_income_code + female +
        age_band, data = trans_level2)

Residuals:
     Min       1Q   Median       3Q      Max
-0.62735 -0.09321 -0.02713  0.02258  1.17781

Coefficients:
                    Estimate  Std. Error t value Pr(>|t|)
(Intercept)      -0.07635747  0.00665133 -11.480  < 2e-16 ***
bops              0.36904126  0.05107061   7.226 4.97e-13 ***
logprice          0.03706413  0.00036192 102.409  < 2e-16 ***
product_category -0.00075432  0.00005311 -14.204  < 2e-16 ***
f_store6          0.02890149  0.00524564   5.510 3.60e-08 ***
f_store5998      -0.14716693  0.02607943  -5.643 1.67e-08 ***
f_month2         -0.04043300  0.00200233 -20.193  < 2e-16 ***
f_month3         -0.02814154  0.00274077 -10.268  < 2e-16 ***
f_month4         -0.02016118  0.00185282 -10.881  < 2e-16 ***
f_month5         -0.04500864  0.00196522 -22.903  < 2e-16 ***
f_month6         -0.03397232  0.00267187 -12.715  < 2e-16 ***
f_month7         -0.04315030  0.00294558 -14.649  < 2e-16 ***
f_month8         -0.02105389  0.00212501  -9.908  < 2e-16 ***
f_month9         -0.04828603  0.00383782 -12.582  < 2e-16 ***
f_month10        -0.04478738  0.00385257 -11.625  < 2e-16 ***
f_month11        -0.06218424  0.00439275 -14.156  < 2e-16 ***
f_month12        -0.07446752  0.00465185 -16.008  < 2e-16 ***
f_year2012       -0.05514420  0.00678403  -8.129 4.35e-16 ***
f_year2013       -0.06034666  0.00730686  -8.259  < 2e-16 ***
est_income_code   0.00232129  0.00020260  11.457  < 2e-16 ***
female            0.01746318  0.00194665   8.971  < 2e-16 ***
age_band          0.00020169  0.00020437   0.987    0.324
```

```
Diagnostic tests:
                   df1    df2 statistic  p-value
Weak instruments     2 987076    121.89  < 2e-16 ***
Wu-Hausman           1 987076     59.84 1.03e-14 ***
Sargan               1     NA      1.95    0.163
---
Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1

Residual standard error: 0.3318 on 987077 degrees of freedom
Multiple R-Squared: -0.215,	Adjusted R-squared: -0.215
Wald test: 931.7 on 21 and 987077 DF,  p-value: < 2.2e-16
```

```
==========================================================
                           Dependent variable:
                    --------------------------------------
                                   return
                    Regression Results: Endogeneity
----------------------------------------------------------
bops                             0.369***
                                 (0.051)

logprice                         0.037***
                                (0.0004)

product_category                -0.001***
                                (0.0001)

f_store6                         0.029***
                                 (0.005)

f_store5998                     -0.147***
                                 (0.026)

f_month2                        -0.040***
                                 (0.002)
```

Analysis: Product level – Sales

Negative Binomial Results

	Dependent variable:	
	salesquantity	
	Normal SE	HW-Robust SE
	(1)	(2)
BIE_timeline_PC	1.391***	1.391***
	(0.040)	(0.077)
group_store_PC	12.415***	12.415***
	(0.035)	(0.070)
factor_PC2	2.082***	2.082***
	(0.046)	(0.091)
factor_Month10	0.952	0.952
	(0.043)	(0.079)
factor_Month11	1.592***	1.592***
	(0.041)	(0.074)
factor_Month12	2.941***	2.941***
	(0.039)	(0.073)
BIE_timeline_PC:group_store_PC	0.683***	0.683***
	(0.044)	(0.083)
Constant	1.242**	1.242**
	(0.070)	(0.164)
Observations	21,115	21,115
Log Likelihood	-87,498.720	-87,498.720
theta	0.740*** (0.007)	0.740*** (0.007)
Akaike Inf. Crit.	175,071.400	175,071.400
Note:	*p<0.05; **p<0.01; ***p<0.001	

```
Likelihood ratio test

Model 1: salesquantity ~ BIE_timeline_PC * group_store_PC + factor_PC +
    avg_female + avg_age + avg_income + avg_homeowner + avg_childowner +
    factor_Month
Model 2: salesquantity ~ 1
  #Df LogLik  Df Chisq Pr(>Chisq)
1  38 -87498
2   2 -96093 -36 17190  < 2.2e-16 ***
---
Signif. codes:  0 ‘***’ 0.001 ‘**’ 0.01 ‘*’ 0.05 ‘.’ 0.1 ‘ ’ 1
```

OLS Regression results

	Dependent variable:	
	log_salesvalue	
	Normal SE	HW-Robust SE
	(1)	(2)
BIE_timeline_PC	0.265***	0.265***
	(0.051)	(0.077)
group_store_PC	1.565***	1.565***
	(0.045)	(0.070)
factor_PC2	-1.197***	-1.197***
	(0.061)	(0.091)
factor_Month11	0.413***	0.413***
	(0.055)	(0.074)
factor_Month12	1.003***	1.003***
	(0.053)	(0.073)
BIE_timeline_PC:group_store_PC	-0.288***	-0.288***
	(0.056)	(0.083)
Constant	6.996***	6.996***
	(0.092)	(0.164)
Observations	21,115	21,115
R2	0.323	0.323
Adjusted R2	0.322	0.322
Residual Std. Error	1.607	1.607
F Statistic	279.284***	279.284***

Analysis: Product level – Returns

Negative Binomial Results

	Dependent variable: returnquantity	
	Normal SE	HW-Robust SE
	(1)	(2)
BIE_timeline_PC	1.518***	1.518***
	(0.058)	(0.077)
group_store_PC	6.084***	6.084***
	(0.051)	(0.070)
factor_PC2	1.279***	1.279***
	(0.047)	(0.091)
factor_Month12	1.072	1.072
	(0.043)	(0.073)
BIE_timeline_PC:group_store_PC	0.615***	0.615***
	(0.061)	(0.083)
Constant	0.468***	0.468***
	(0.082)	(0.164)
Observations	21,115	21,115
Log Likelihood	-43,322.610	-43,322.610
theta	0.905*** (0.014)	0.905*** (0.014)
Akaike Inf. Crit.	86,717.220	86,717.220
Note:	*p<0.05; **p<0.01; ***p<0.001	

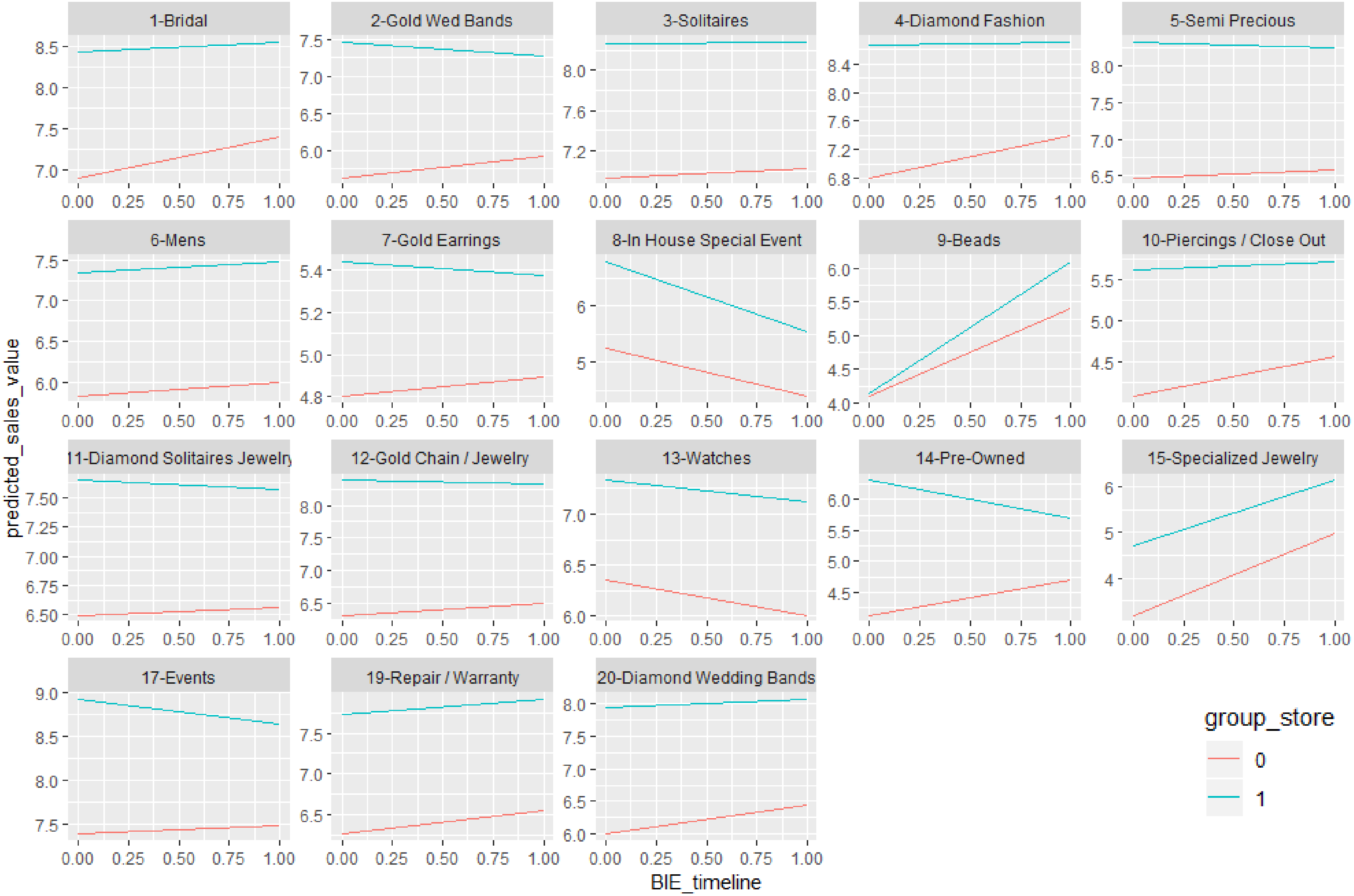
```
Likelihood ratio test

Model 1: returnquantity ~ BIE_timeline_PC * group_store_PC + factor_PC +
    salesquantity + avg_female + avg_age + avg_income + factor_Month
Model 2: returnquantity ~ 1
  #Df LogLik  Df Chisq Pr(>Chisq)
1  37 -43322
2   2 -51169 -35 15694  < 2.2e-16 ***
---
Signif. codes:  0 ‘***’ 0.001 ‘**’ 0.01 ‘*’ 0.05 ‘.’ 0.1 ‘ ’ 1
```

OLS Regression Results

	Dependent variable: log_returnvalue	
	Normal SE	HW-Robust SE
	(1)	(2)
BIE_timeline_PC	0.236***	0.236**
	(0.070)	(0.077)
group_store_PC	1.271***	1.271***
	(0.064)	(0.070)
factor_Month12	-0.546***	-0.546***
	(0.074)	(0.073)
BIE_timeline_PC:group_store_PC	-0.333***	-0.333***
	(0.078)	(0.083)
Constant	-7.316***	-7.316***
	(0.142)	(0.164)
Observations	21,115	21,115
R2	0.604	0.604
Adjusted R2	0.603	0.603
Residual Std. Error	2.218	2.218
F Statistic	918.503***	918.503***
Note:	*p<0.05; **p<0.01; ***p<0.001	

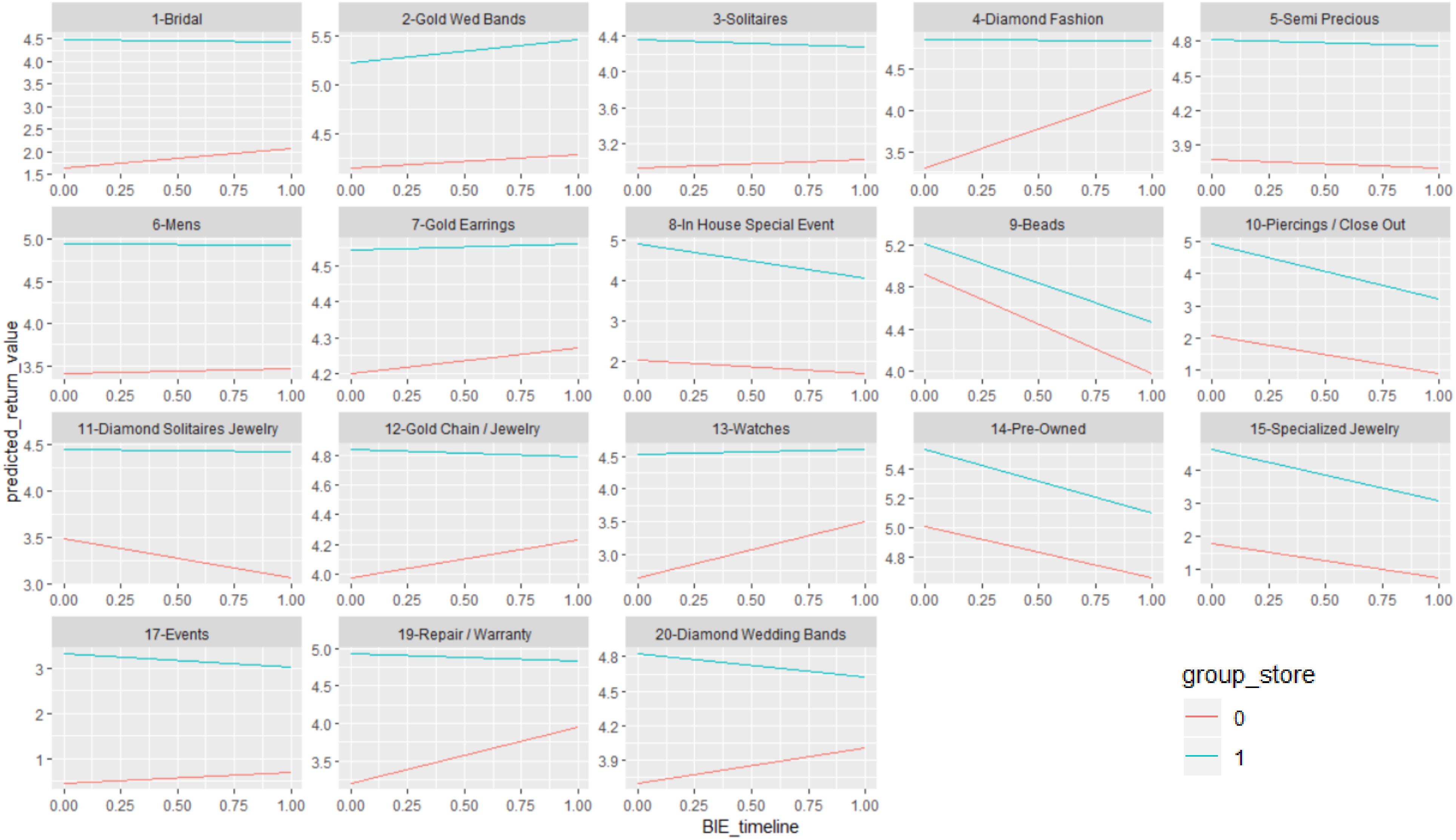
```
> bptest(ols54) # Breusch-Pagan test indicates heteroskedasticity

	studentized Breusch-Pagan test

data:  ols54
BP = 3378.7, df = 35, p-value < 2.2e-16
```

Online Sales– Product Level



Product Category	Increase/ Decrease
1	**- 31.3% *****
2	**- 38.8% *****
3	**- 6.4% *****
4	**- 62% *****
5	**- 27.2% *****
6	**- 3.1%**
7	**- 0.5%**
8	**NA**
9	**+ 35% *****
10	**NA**
11	**- 16.9% *****
12	**- 31.7% *****
13	**+ 12.2% *****
14	**- 114% *****
15	**NA**
16	**NA**
17	**NA**
18	**NA**
19	**NA**
20	**- 5.7% *****
21	**- 39.3% *****

Online Returns – Product Level



Product Category	Increase/ Decrease
1	-42.9%***
2	+19.1%***
3	-93.9%***
4	-95%**
5	-1.2%
6	-1.7%
7	-0.43
8	NA
9	-49.3%***
10	NA
11	+37.4%***
12	-34.6%***
13	-81.3%***
14	-41.4%***
15	NA
16	NA
17	NA
18	NA
19	NA
20	-92.7%***
21	-54.0%***