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Background

We are given six questions from our boss to assess whether or not to implement BOPS.

Given 4 datasets to compare BOPS and BO-Delivery from August 1, 2010 - July 31, 2013:

1. Transaction Level Data
2. Consumer Level Data
3. Online Daily Data - Sales and Return
4. Online Daily Data - Product Category Sales and Return

Background

There are three online channel stores:

- Store #2
- Store #6
- Store #5998

Implementation of BOPS

- Stores 2 and 6 implemented BOPS on August 1st, 2011
- Store 5998 implemented BOPS on September 27th, 2012
    - The difference is 1 year, 1 month and 27 days.

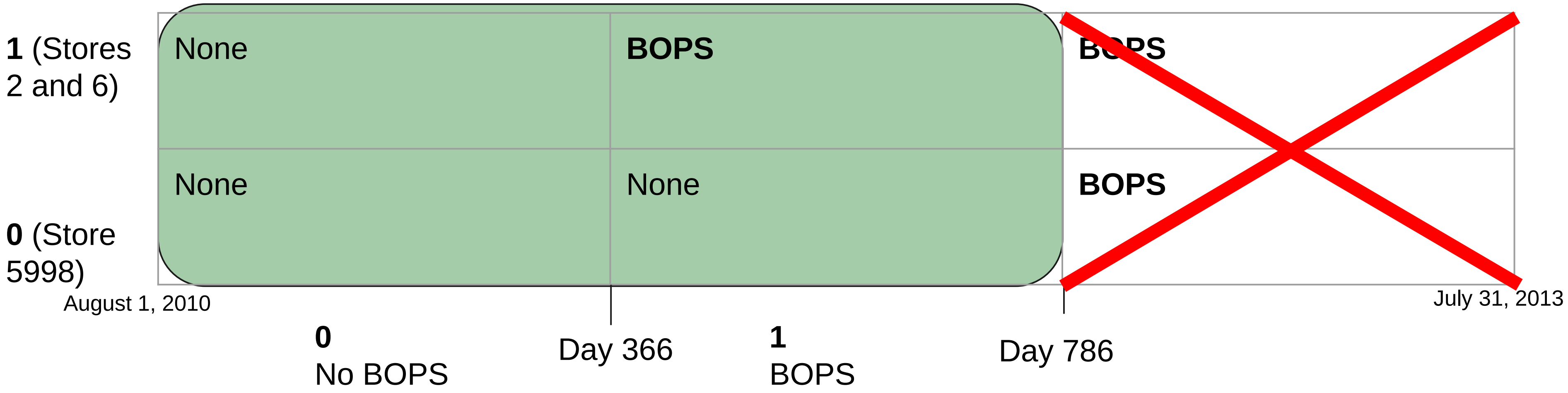
Purpose of Analysis

In particular, we are interested in:

- Impact of BOPS on online sales and returns (Q1 and Q2)
- Impact of BOPS on online customer behavior (Q3 and Q4)
- Product-level impact of BOPS implementation (Q5 and Q6)

Standardization of Time

Dataset - Online Daily Sales Return



Question 1 -What is the impact of implementing BOPs strategy on online sales?

Dataset - Online Daily Sales Return

Model: OLS

$$log(Y_{Sales\ Value}) = \beta_0 + \beta_1\ Time\_dummy*Storegroup + \beta_2\ Avg\_female + \beta_3\ Avg\_age + \beta_4\ Avg\_income + \beta_5\ Avg\_homeowner + \beta_6\ Avg\_residency + \beta_7 Avg\_childowner$$

Model: Negative Binomial

$$log(Y_{Sales\ Quantity}) = \beta_0 + \beta_1\ Time\_dummy*Storegroup + \beta_2\ Avg\_female + \beta_3\ Avg\_age + \beta_4\ Avg\_income + \beta_5\ Avg\_homeowner + \beta_6\ Avg\_residency + \beta_7 Avg\_childowner$$

Question 2 -What is the impact of implementing BOPs strategy on online return?

Model: OLS

$$log(Y_{Return\ Value}) = \beta_0 + \beta_1\ Time\_dummy*Storegroup + \beta_2\ Avg\_female + \beta_3\ Avg\_age + \beta_4\ Avg\_income + \beta_5\ Avg\_homeowner + \beta_6\ Avg\_residency + \beta_7\ Avg\_childowner + \beta_8 SalesValue$$

Model: Negative Binomial

$$log(Y_{Return\ Quantity}) = \beta_0 + \beta_1\ Time\_dummy*Storegroup + \beta_2\ Avg\_female + \beta_3\ Avg\_age + \beta_4\ Avg\_income + \beta_5\ Avg\_homeowner + \beta_6\ Avg\_residency + \beta_7\ Avg\_childowner + \beta_8 SalesQuantity$$

Q1 Sales Value

Regression Results

	Dependent variable:
	LogSalesValue HW-Robust SE
final_day	0.26*
	(0.13)
storegroup	1.90***
	(0.14)
avg_female	-1.52**
	(0.47)
avg_age	-0.16**
	(0.05)
avg_income	0.32**
	(0.10)
avg_homeowner	-0.26
	(0.48)
avg_residency	-0.07
	(0.04)
avg_childowner	0.62
	(0.62)
final_day:storegroup	-0.41*
	(0.17)
Constant	8.80***
	(0.65)
Observations	2,005
R2	0.14
Adjusted R2	0.13
Residual Std. Error	2.01
F Statistic	35.63***
Note:	*p<0.05; **p<0.01; ***p<0.001

Q1 Sales Quantity

Sales Quantity Negative Binomial

	Dependent variable:
	salesquantity HW-Robust SE
final_day	1.21
	(0.13)
storegroup	15.07***
	(0.13)
avg_female	0.11***
	(0.23)
avg_age	0.85***
	(0.02)
avg_income	1.37***
	(0.04)
avg_homeowner	0.85
	(0.20)
avg_residency	0.98
	(0.02)
avg_childowner	0.61*
	(0.24)
final_day:storegroup	0.78
	(0.15)
Constant	89.66***
	(0.32)
Observations	2,005
Log Likelihood	-13,395.60
theta	0.58*** (0.02)
Akaike Inf. Crit.	26,811.19
Note:	*p<0.05; **p<0.01; ***p<0.001

For stores that have BOPs implemented, there is a decrease in 41% in sales value.

(IRR) Interpretation: For stores that have BOPs implemented, there is a no significant change in sales quantity.

Q2 Return Value

Return Value Results

	Dependent variable:
	LogReturnValue HW-Robust SE
final_day	0.94*** (0.25)
storegroup	2.07*** (0.25)
salesvalue	0.0000*** (0.0000)
avg_female	0.09 (0.55)
avg_age	-0.14* (0.06)
avg_income	0.29* (0.11)
avg_homeowner	-0.10 (0.57)
avg_residency	-0.11* (0.05)
avg_childowner	1.08 (0.68)
final_day:storegroup	-1.20*** (0.28)
Constant	4.57*** (0.74)
Observations	2,005
R2	0.37
Adjusted R2	0.36
Residual Std. Error	2.47
F Statistic	115.74***
Note:	*p<0.05; **p<0.01; ***p<0.001

For stores that have BOPs implemented, there is a 120% decrease in return value.

Q2 Return Quantity

Return Quantity Exponentiated Negative Binomial

	Dependent variable:
	returnquantity HW-Robust SE
final_day	1.49*** (0.13)
storegroup	4.55*** (0.13)
salesquantity	1.00***
avg_female	0.75* (0.23)
avg_age	0.90*** (0.02)
avg_income	1.16*** (0.04)
avg_homeowner	0.69* (0.20)
avg_residency	0.98 (0.02)
avg_childowner	1.45* (0.24)
final_day:storegroup	0.60*** (0.15)
Constant	3.21*** (0.32)
Observations	2,005
Log Likelihood	-8,127.20
theta	1.06*** (0.04)
Akaike Inf. Crit.	16,276.41
Note:	*p<0.05; **p<0.01; ***p<0.001

(IRR): For stores that have BOPs implemented, there is a 40% decrease in return quantity.

Question 3 - What is the impact of using the BOPS service on online customer purchase behavior?

Dataset - Consumer Level Data

Model: Negative Binomial, Dependent Variable: Sales Quantity

$$Y_{Sales\ Quantity} = \beta_0 + \beta_1 Bops\_in\_effect*Bops\_user + \beta_2 Avg\_female + \beta_3 Avg\_age + \beta_4 Avg\_income + \beta_5 Avg\_homeowner + \beta_6 Avg\_residency + \beta_7 Avg\_childowner$$

Model: OLS, Dependent Variable: Log(Sales Value + 1)

$$\log(Y_{Sales\ Value}) = \beta_0 + \beta_1 Bops\_in\_effect*Bops\_user + \beta_2 Avg\_female + \beta_3 Avg\_age + \beta_4 Avg\_income + \beta_5 Avg\_homeowner + \beta_6 Avg\_residency + \beta_7 Avg\_childowner$$

Q3 Sales Value

Sales Value Regression Results

	Dependent variable:	
	log(1 + salesvalue)	
	Normal SE	HW-Robust SE
	(1)	(2)
bops_in_effect	0.033***	0.033***
	(0.008)	(0.008)
bops_user	-0.208***	-0.208***
	(0.013)	(0.013)
dummy_homeowner_code	0.029**	0.029**
	(0.009)	(0.009)
dummy_child	-0.037***	-0.037***
	(0.008)	(0.008)
age_band	0.005***	0.005***
	(0.001)	(0.001)
est_income_code	0.009***	0.009***
	(0.002)	(0.002)
length_of_residence	-0.001	-0.001
	(0.001)	(0.001)
female	-0.111***	-0.111***
	(0.008)	(0.008)
bops_in_effect:bops_user	0.084***	0.084***
	(0.019)	(0.019)
Constant	5.318***	5.318***
	(0.013)	(0.012)
Observations	84,420	84,420
R2	0.008	0.008
Adjusted R2	0.008	0.008
Residual Std. Error	1.067	1.067
F Statistic	79.147***	79.147***
Note:	*p<0.05; **p<0.01; ***p<0.001	

Interpretation: For a one unit increase in bops user when bops is in effect, expected sales value increases by 8.4%

Q3 Sales Quantity

Sales Quantity Regression Results

	Dependent variable:
	salesquantity
	Model-5 NB
bops_in_effect	1.10***
	(0.01)
bops_user	1.01
	(0.01)
dummy_homeowner_code	1.02**
	(0.01)
dummy_child	0.99
	(0.01)
age_band	0.99***
	(0.001)
est_income_code	1.02***
	(0.002)
length_of_residence	1.00***
	(0.001)
female	1.46***
	(0.01)
bops_in_effect:bops_user	1.18***
	(0.02)
Constant	1.77***
	(0.01)
Observations	84,420
Log Likelihood	-171,096.20
theta	2.00*** (0.01)
Akaike Inf. Crit.	342,212.30
Note:	*p<0.05; **p<0.01; ***p<0.001

(IRR): For a one unit increase in bops user when bops is in effect, the expected count increases by 18%

Question 4 - What is the impact of using the BOPS service on online customer return behavior?

We expect customers <u>using BOPS</u> to have an <u>increased likelihood of returning their purchase</u>.

*To assess this hypothesis, we use **transaction level data** to analyze, since it holds information on customers, purchase delivery method (BOPS vs home delivery), and purchase return information and also address endogeniety.*

Conceptual model:

$$Y_{Return} = \beta_0 + \beta_1 BOPS + \beta_2 log(Price) + \beta_3 Store\ Number + \beta_4 Age\ Band + \beta_5 Month + \beta_6 Year + \beta_6 Product\ Category + \beta_6 Age\ Band + \beta_7 Female + \beta_8 Has\ Child$$

[Link to summary statistics]

Estimation results

$$Y_{Return} = \beta_0 + \beta_1 \mathbf{BOPS} + \sum \beta_i Controls$$

$$X_1 = \gamma_0 + \gamma_1 \mathbf{Length\ of\ Residence} + \sum \gamma_j Controls$$

Note: 2SLS model used in estimation

A transaction using BOPS service is associated with **an <u>increase of 18 percentage points</u> in likelihood of product returns**

Regression Results

	Dependent variable:	
	return	
	Normal SE	HW-Robust SE
	(1)	(2)
bops	$\boxed{0.189^{***}}$	$\boxed{0.189^{***}}$
	$\boxed{(0.057)}$	$\boxed{(0.057)}$
Observations	1,170,564	1,170,564
R2	-0.030	-0.030
Adjusted R2	-0.030	-0.030
Residual Std. Error	0.304	0.304
Note:	*p<0.05; **p<0.01; ***p<0.001	

Note: Control variables omitted for brevity

Link to full model output

Question 5 -What is the impact of implementing BOPS strategy on product-level sales and return?

Dataset - Online Daily Product Category Sales/Return

Model: OLS

$log(Y_{Sales\ Value}) = \beta_0 + \beta_1\ Time\_dummy*Storegroup + \beta_2\ Avg\_female + \beta_3\ Avg\_age + \beta_4\ Avg\_income + \beta_5\ Avg\_homeowner + \beta_6\ Avg\_residency + \beta_7\ Avg\_childowner + \beta_8\ Product\ Category$

Model: Negative Binomial

$log(Y_{Sales\ Quantity}) = \beta_0 + \beta_1\ Time\_dummy*Storegroup + \beta_2\ Avg\_female + \beta_3\ Avg\_age + \beta_4\ Avg\_income + \beta_5\ Avg\_homeowner + \beta_6\ Avg\_residency + \beta_7\ Avg\_childowner + \beta_8\ Product\ Category$

Model: OLS

$log(Y_{Return\ Value}) = \beta_0 + \beta_1\ Time\_dummy*Storegroup + \beta_2\ Avg\_female + \beta_3\ Avg\_age + \beta_4\ Avg\_income + \beta_5\ Avg\_homeowner + \beta_6\ Avg\_residency + \beta_7\ Avg\_childowner + \beta_8\ Product\ Category + \beta_9\ SalesValue$

Model: Negative Binomial

$log(Y_{Return\ Quantity}) = \beta_0 + \beta_1\ Time\_dummy*Storegroup + \beta_2\ Avg\_female + \beta_3\ Avg\_age + \beta_4\ Avg\_income + \beta_5\ Avg\_homeowner + \beta_6\ Avg\_residency + \beta_7\ Avg\_childowner + \beta_8\ Product\ Category + \beta_9\ SalesQuantity$

Q5 Sales Value

	Dependent variable: Logsalesvalue HW-Robust SE
final_day	0.18*** (0.04)
storegroup	1.47*** (0.04)
product_category	-0.01*** (0.002)
avg_female	-1.06*** (0.07)
avg_age	-0.06*** (0.01)
avg_income	0.10*** (0.02)
avg_homeowner	-0.13 (0.09)
avg_residency	-0.01* (0.01)
avg_childowner	0.01 (0.08)
final_day:storegroup	-0.20*** (0.05)
Constant	7.00*** (0.11)
Observations	21,003
R2	0.11
Adjusted R2	0.11
Residual Std. Error	1.84
F Statistic	256.84***
Note:	*p<0.05; **p<0.01; ***p<0.001

For stores that have implemented BOPS, there is a 20% decrease in sales value.

Q5 Sales Quantity

Sales Quantity Negative Binomial

	Dependent variable: salesquantity HW-Robust
final_day	1.30*** (0.06)
storegroup	10.46*** (0.05)
product_category	1.02*** (0.002)
avg_female	0.63*** (0.05)
avg_age	0.87*** (0.01)
avg_income	1.47*** (0.02)
avg_homeowner	1.23*** (0.06)
avg_residency	1.05*** (0.004)
avg_childowner	0.97 (0.05)
final_day:storegroup	0.78*** (0.07)
Constant	0.97 (0.14)
Observations	21,003
Log Likelihood	-92,659.94
theta	0.49*** (0.004)
Akaike Inf. Crit.	185,341.90
Note:	*p<0.05; **p<0.01; ***p<0.001

(IRR)Interpretation: For stores that have implemented BOPS, there is a 22% decrease in sales quantity.

Q5 Return Value

Return Value

	Dependent variable:
	Logreturnvalue HW-Robust
final_day	0.40*** (0.08)
storegroup	2.43*** (0.08)
product_category	-0.01 (0.003)
avg_female	0.22* (0.09)
avg_age	-0.10*** (0.01)
avg_income	0.12*** (0.02)
avg_homeowner	-0.19 (0.12)
avg_residency	-0.03** (0.01)
avg_childowner	0.01 (0.11)
salesvalue	0.0001*** (0.0000)
final_day:storegroup	-0.60*** (0.09)
Constant	1.59*** (0.15)
Observations	21,003
R2	0.31
Adjusted R2	0.31
Residual Std. Error	2.92
F Statistic	863.34***
Note:	*p<0.05; **p<0.01; ***p<0.001

Q5 Return Quantity

Return Quantity Negative Binomial

	Dependent variable:
	returnquantity HW-Robust
final_day	1.46*** (0.06)
storegroup	5.34*** (0.05)
product_category	0.99*** (0.002)
avg_female	1.15*** (0.03)
avg_age	0.92*** (0.004)
avg_income	1.07*** (0.01)
avg_homeowner	0.80*** (0.04)
avg_residency	0.98*** (0.003)
avg_childowner	0.98 (0.03)
salesquantity	1.01*** (0.0000)
final_day:storegroup	0.66*** (0.06)
Constant	0.54*** (0.06)
Observations	21,003
Log Likelihood	-44,007.13
theta	0.78*** (0.01)
Akaike Inf. Crit.	88,038.26
Note:	*p<0.05; **p<0.01; ***p<0.001

Interpretation: For stores that have implemented BOPS, there is a 60% decrease in return value.

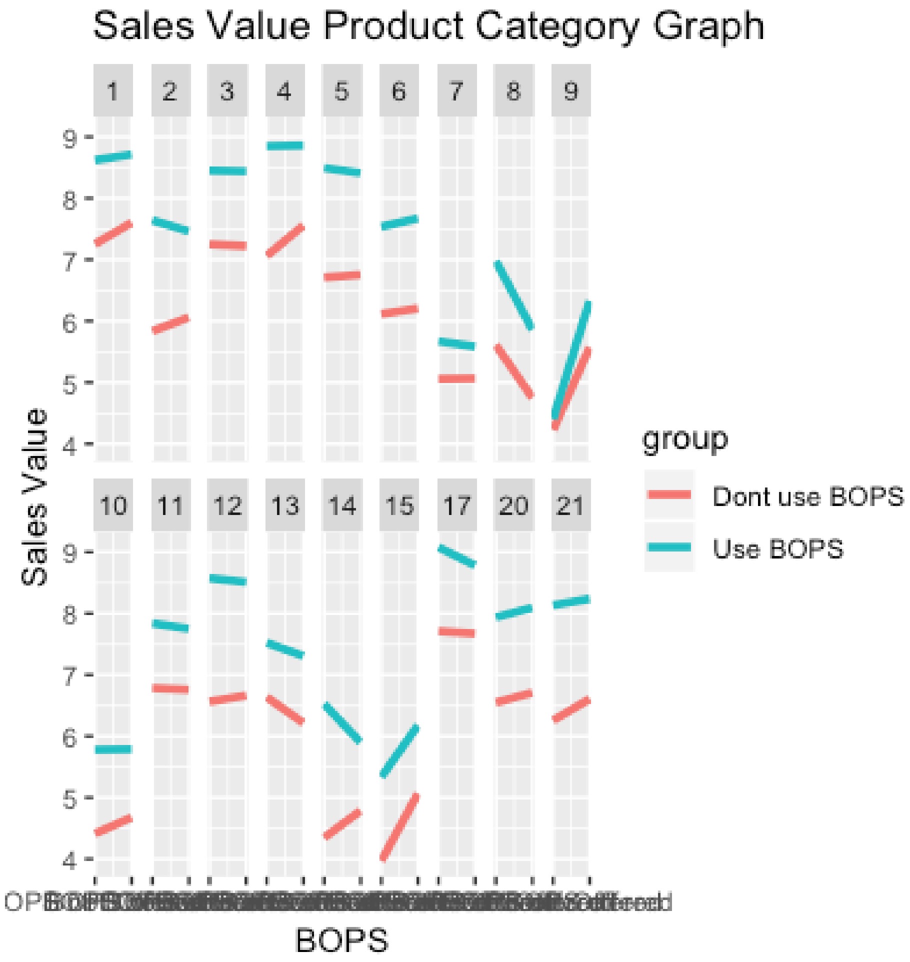
(IRR): For stores that have implemented BOPS, there is a 34% decrease in return quantity.

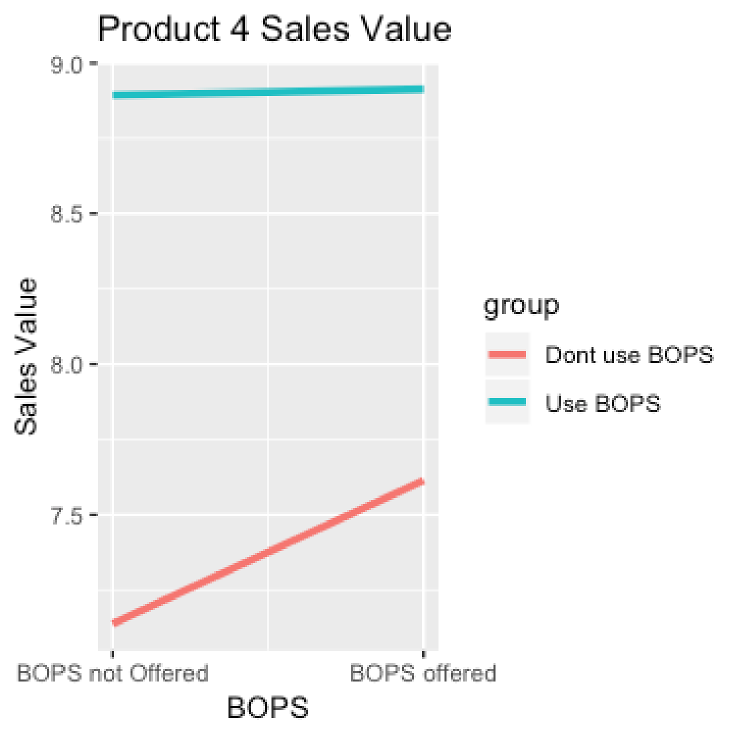
Q6 - Sales Value

*The marginal effect plots for all product categories **Sales Value***

*We found that **only 2 out of the 21** categories have a significant difference.*

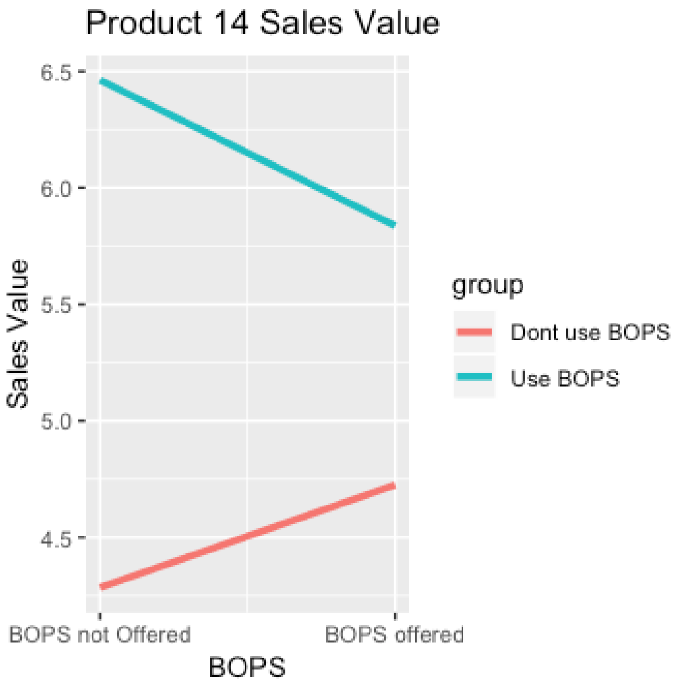
1. *Product #4 (Diamond Fashion)*
2. *Product #14 (Pre-Owned)*






```
final_day:storegroup          -0.46**
                              (0.15)
```

Interpretation: When BOPS is available and in use, it led to a decrease of 46% in sales value for Diamond Fashion products




```
final_day:storegroup          -1.06***
                              (0.19)
```

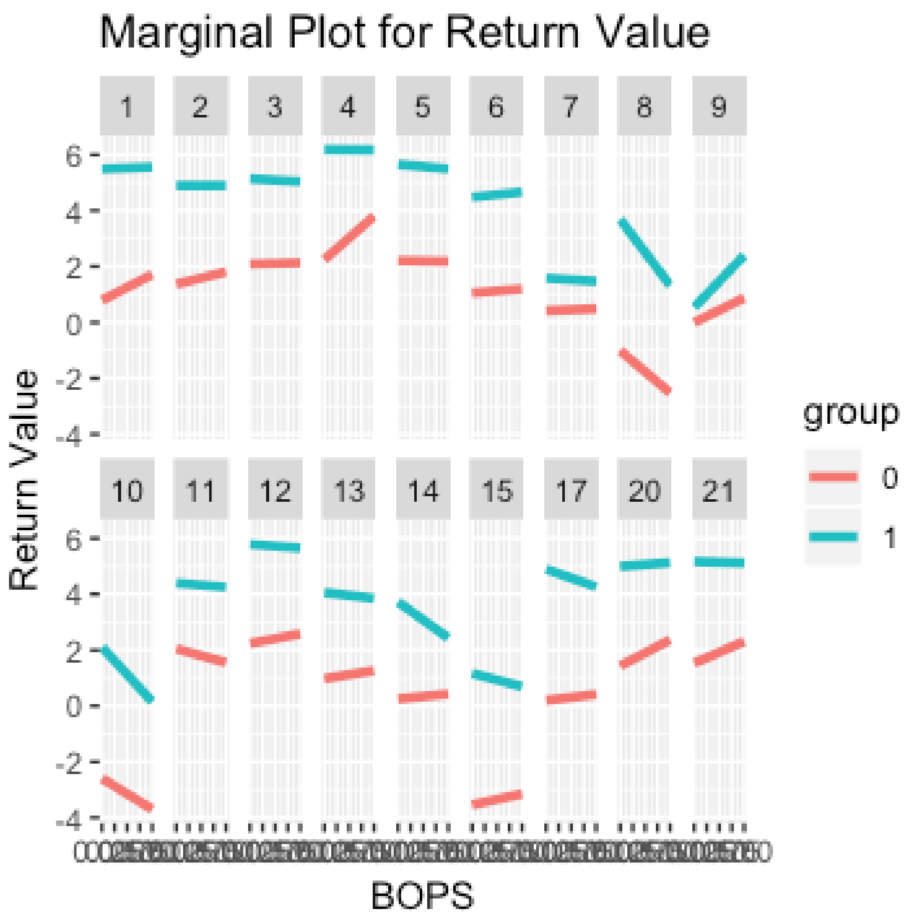
Interpretation: When BOPS is available and in use, it led to a decrease of 106% in sales value for Pre-Owned products

Q6 - Return Value

The Marginal plot for all categories
Return Value

*We found that **3 out of the 21** categories have a significant difference*

1. *Product #4 (Diamond Fashion)*
2. *Product #14 (Pre-Owned)*
3. *Product #21 (Sterling Silver)*

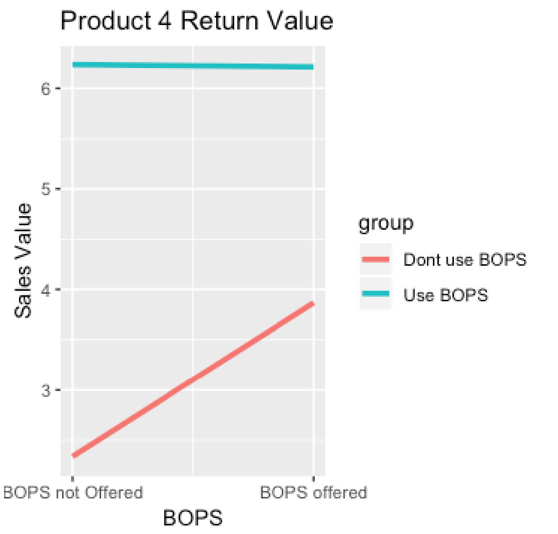


Product Categories with Significant Changes With BOPS:

In these product categories, the use of BOPS led to a decrease of 155%, 148%, and 90% in sales value.

Category 4

```
final_day:storegroup          -1.55***
                               (0.34)
```

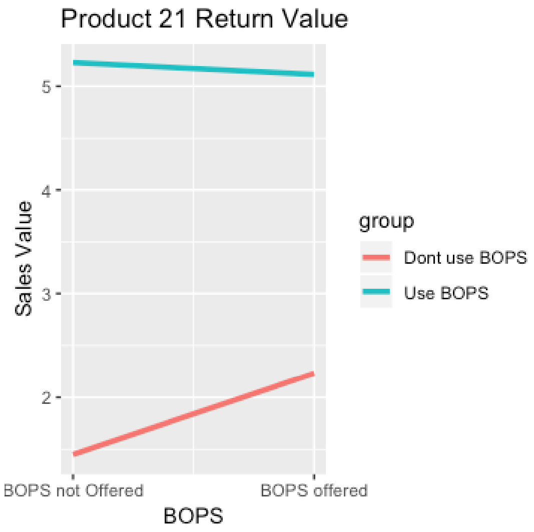


Category 14

```
final_day:storegroup          -1.48***
                               (0.29)
```

Category 21

```
final_day:storegroup          -0.90**
                               (0.30)
```



To recap

Question	Model	Outcome	Dataset
Q1 - Impact of BOPs on online channel sales.	OLS	**Decrease in sales value by 40%.** **No change in sales quantity.**	**Online Daily Data - Sales and Return**
Q2 - Impact of BOPs on online channel returns.	Negative Binomial	**Decrease in return value by 120%** **Decrease in return quantity by 40%.**	**Online Daily Data - Sales and Return**
Q3 - Impact of using BOPS service on online customer purchase behavior.	OLS and Neg Bin	**Increase in sales value by 8.4%** **Increase in sales quantity by 18%**	**Consumer Level Data**
Q4 - Impact of using BOPs service on online customer return behavior.	OLS, Probit, and IV/2SLS	**Increase in return likelihood by 18 p.p.**	**Transaction Level Data**
Q5 - Impact of implementing BOPS strategy on product level sales and returns.	OLS and Neg Bin	**Decrease in sales value by 20% and 22% in sales quantity. Decrease in return value by 60% and 34% decrease in return quantity.**	**Online Daily Data - Product Category**
Q6 - Impact of implementing BOPS strategy vary across product categories.	OLS	**The effect of implementing BOPS strategy depends on product category number.**	**Online Daily Data - Product Category**

Managerial Insight

- We **do not recommend** a universal BOPS rollout because the effects differ at different levels of analysis:
    - Limit BOPS to loyal customers since repeat customers bought more when using BOPS.
    - Target specific product categories such as product #21, sterling silver
    - We gather more data on online user transaction
        - ROPO - Research Online, Purchase Offline
    - We gather more data on more channels that have implemented BOPS

Limitations

- We don't know how much the implementation of BOPS costs and if it is scalable.
    - If implementation of BOPS results in insignificant change in net profits, implementation results in a loss.
- We indicate that a consumer uses BOPS due to convenience (near the store), however we do not have any data of how far consumers are from the store
    - Person using BOPS likely lives near store, making it convenient for them to return in store (vs by mail). Dataset lacks distance to store information.
- We don't know if customer returns are converted to in-store credit or exchange.
    - Without this information, we could be overestimating effect of BOPS on returns.
- We were not given full details on the return policy of the stores and online channels
- Cost for customers to use BOPS versus being delivered

Appendix

Summary Statistics - Online Daily Returns/Sales before replacing NA with mean

Online Sales and Return Level Descriptive Statistics

Statistic	N	Mean	St. Dev.	Min	Pctl(25)	Median	Pctl(75)	Max
store_number	2,005	1,579.44	2,639.11	2	2	6	5,998	5,998
year	2,005	2,011.18	0.70	2,010	2,011	2,011	2,012	2,012
month_index	2,005	25.78	7.26	13	20	26	32	38
month_dummy	2,005	6.62	3.41	1	4	7	9	12
bops_in_effect	2,005	0.39	0.49	0	0	0	1	1
day	2,005	404.81	221.04	1	215	411	593	785
salesvalue	2,005	91,493.44	164,109.90	0.00	7,248.05	16,249.74	148,777.00	1,413,919.00
returnvalue	2,005	14,406.62	24,454.22	0.00	681.43	2,387.69	24,014.74	192,876.80
salesquantity	2,005	523.04	989.23	1	38	98	760	8,933
returnquantity	2,005	55.16	97.77	0	3	10	88	876
avg_female	1,583	0.52	0.18	0.00	0.47	0.53	0.60	1.00
avg_age	1,634	5.07	1.67	0.00	4.64	5.05	5.64	13.00
avg_income	1,633	5.38	0.89	1.00	5.17	5.40	5.57	9.00
avg_homeowner	1,633	0.66	0.19	0.00	0.62	0.67	0.72	1.00
avg_residency	1,633	7.06	2.13	0.00	6.66	7.04	7.48	15.00
avg_childowner	1,633	0.35	0.17	0.00	0.33	0.36	0.40	1.00
LogSalesValue	2,005	9.85	2.16	0.00	8.89	9.70	11.91	14.16
LogReturnValue	2,005	7.42	3.10	0.00	6.53	7.78	10.09	12.17
LogSalesQuantity	2,005	4.73	1.99	0.00	3.64	4.58	6.63	9.10
LogReturnQuantity	2,005	2.67	1.74	0.00	1.39	2.40	4.49	6.78
final_day	2,005	0.56	0.50	0	0	1	1	1
storegroup	2,005	0.74	0.44	0	0	1	1	1

Summary Statistics - Replace NA with Average

Online Sales and Return Level Descriptive Statistics

Statistic	N	Mean	St. Dev.	Min	Pctl(25)	Median	Pctl(75)	Max
store_number	2,005	1,579.44	2,639.11	2	2	6	5,998	5,998
year	2,005	2,011.18	0.70	2,010	2,011	2,011	2,012	2,012
month_index	2,005	25.78	7.26	13	20	26	32	38
month_dummy	2,005	6.62	3.41	1	4	7	9	12
bops_in_effect	2,005	0.39	0.49	0	0	0	1	1
day	2,005	404.81	221.04	1	215	411	593	785
salesvalue	2,005	91,493.44	164,109.90	0.00	7,248.05	16,249.74	148,777.00	1,413,919.00
returnvalue	2,005	14,406.62	24,454.22	0.00	681.43	2,387.69	24,014.74	192,876.80
salesquantity	2,005	523.04	989.23	1	38	98	760	8,933
returnquantity	2,005	55.16	97.77	0	3	10	88	876
avg_female	2,005	0.52	0.16	0.00	0.49	0.53	0.57	1.00
avg_age	2,005	5.03	1.51	0.00	4.73	4.87	5.49	13.00
avg_income	2,005	5.37	0.81	1.00	5.24	5.34	5.52	9.00
avg_homeowner	2,005	0.66	0.17	0.00	0.64	0.66	0.70	1.00
avg_residency	2,005	7.04	1.92	0.00	6.75	7.00	7.33	15.00
avg_childowner	2,005	0.36	0.15	0.00	0.34	0.37	0.39	1.00
LogSalesValue	2,005	9.85	2.16	0.00	8.89	9.70	11.91	14.16
LogReturnValue	2,005	7.42	3.10	0.00	6.53	7.78	10.09	12.17
LogSalesQuantity	2,005	4.73	1.99	0.00	3.64	4.58	6.63	9.10
LogReturnQuantity	2,005	2.67	1.74	0.00	1.39	2.40	4.49	6.78
final_day	2,005	0.56	0.50	0	0	1	1	1
storegroup	2,005	0.74	0.44	0	0	1	1	1

Q1 Analysis of Control Variables

1. **Avg_Female -** the ratio of all female customers to all customers
2. **Avg_Age -** average age_band of all customers at the given aggregation level and note that this is not the actual age. It is the average of age groups. The higher it is, the older the customer profile is
3. **Avg_Income -** the average income_band of all customers at the given aggregation level. It is the average of income groups. The higher it is, the richer the customer profile is
4. **Avg_Homeowner -** the ratio of customers who own their house to all customers (homeowners + renters)
5. **Avg_Residency -** the average number of years spent in the current address for customers

   Avg_Childowner - the ratio of customers who have at least one child to all customers

Exclude: Store Number, Year, Product Category, Month, Month_index, Month_dummy, and Bops_In_Effect

Q1 Sales Value/Quantity - Heteroskedasticity

Sales Value

```
> gqtest(sales1)

	Goldfeld-Quandt test

data:  sales1
GQ = 0.61199, df1 = 993, df2 = 992, p-value = 1
alternative hypothesis: variance increases from segment 1 to 2

> bptest(sales1) #Heteroskedastic

	studentized Breusch-Pagan test

data:  sales1
BP = 59.584, df = 9, p-value = 0.000000001612
```

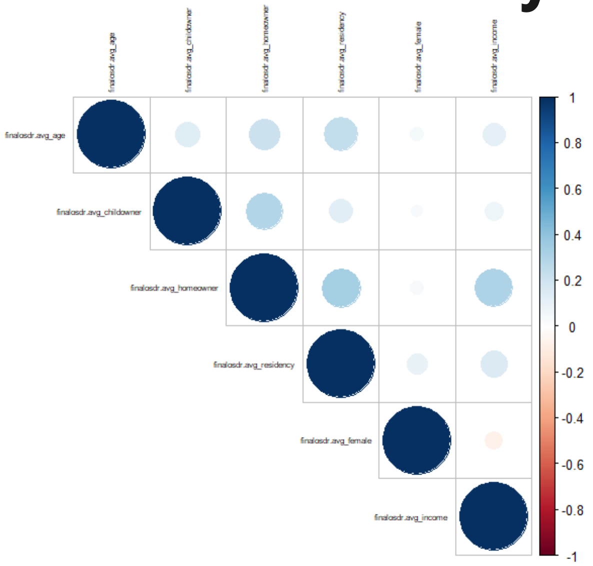
Sales Quantity

```
> gqtest(salesquantnb)

	Goldfeld-Quandt test

data:  salesquantnb
GQ = 0.0044378, df1 = 993, df2 = 992, p-value = 1
alternative hypothesis: variance increases from segment 1 to 2

> bptest(salesquantnb) #Heteroskedastic

	studentized Breusch-Pagan test

data:  salesquantnb
BP = 63.574, df = 9, p-value = 0.000000000273
```

Fixed with HW Robust Standard errors!

Q1/2 - Online Daily Sales/Returns Multicollinearity

```
                          finalosdr.avg_age finalosdr.avg_childowner finalosdr.avg_homeowner finalosdr.avg_residency finalosdr.avg_female
finalosdr.avg_age                 1.0000000               0.13977814              0.21368975              0.24988711           0.04267430
finalosdr.avg_childowner          0.1397781               1.00000000              0.29972108              0.12219873           0.03177948
finalosdr.avg_homeowner           0.2136898               0.29972108              1.00000000              0.33552799           0.03972333
finalosdr.avg_residency           0.2498871               0.12219873              0.33552799              1.00000000           0.09759838
finalosdr.avg_female              0.0426743               0.03177948              0.03972333              0.09759838           1.00000000
finalosdr.avg_income              0.1136697               0.07497034              0.30774555              0.15455566          -0.07291792
                          finalosdr.avg_income
finalosdr.avg_age                   0.11366971
finalosdr.avg_childowner            0.07497034
finalosdr.avg_homeowner             0.30774555
finalosdr.avg_residency             0.15455566
finalosdr.avg_female               -0.07291792
finalosdr.avg_income                1.00000000
> corrplot(corr, type = "upper", tl.pos = "td", method = "circle", tl.cex = 0.5, tl.col = 'black', diag = TRUE)
> #There is no multicollinearity in in demographic variables.
> vifcor(df) # All less than 3 if time variables are not included in data frame.
No variable from the 6 input variables has collinearity problem.

The linear correlation coefficients ranges between:
min correlation ( finalosdr.avg_female ~ finalosdr.avg_childowner ):  0.03177948
max correlation ( finalosdr.avg_residency ~ finalosdr.avg_homeowner ):  0.335528

---------- VIFs of the remained variables --------
                 Variables      VIF
1        finalosdr.avg_age 1.097856
2 finalosdr.avg_childowner 1.106963
3  finalosdr.avg_homeowner 1.330623
4  finalosdr.avg_residency 1.182994
5     finalosdr.avg_female 1.019647
6     finalosdr.avg_income 1.121032
```



Question 3 - Multicollinearity

	consumerdata.store_number	consumerdata.age_band	consumerdata.length_of_residence	consumerdata.bops_in_effect
consumerdata.store_number	1.0000000000	0.000318228	-0.001161459	-0.0005940805
consumerdata.age_band	0.0003182280	1.000000000	0.140020955	0.0000000000
consumerdata.length_of_residence	-0.0011614587	0.140020955	1.000000000	0.0000000000
consumerdata.bops_in_effect	-0.0005940805	0.000000000	0.000000000	1.0000000000
consumerdata.dummy_homeowner_code	-0.0009660944	0.187316469	0.289011449	0.0000000000
consumerdata.dummy_child	-0.0005233652	0.006137120	-0.025386381	0.0000000000
consumerdata.female	-0.0022130349	0.072834704	0.028422111	0.0000000000

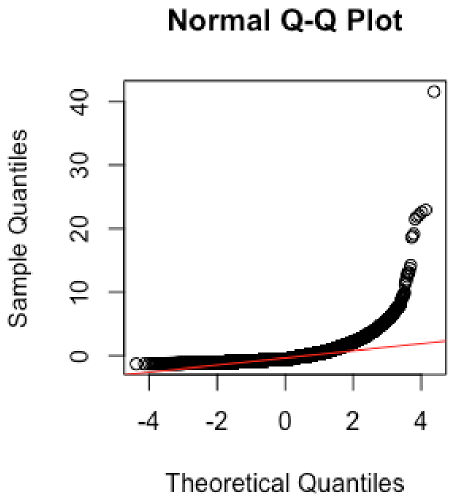
	consumerdata.dummy_homeowner_code	consumerdata.dummy_child	consumerdata.female
consumerdata.store_number	-0.0009660944	-0.0005233652	-0.002213035
consumerdata.age_band	0.1873164691	0.0061371201	0.072834704
consumerdata.length_of_residence	0.2890114486	-0.0253863805	0.028422111
consumerdata.bops_in_effect	0.0000000000	0.0000000000	0.000000000
consumerdata.dummy_homeowner_code	1.0000000000	0.2085613093	0.007922949
consumerdata.dummy_child	0.2085613093	1.0000000000	0.038860043
consumerdata.female	0.0079229486	0.0388600428	1.000000000

Q3 - Sales Quantity, Choosing a Model

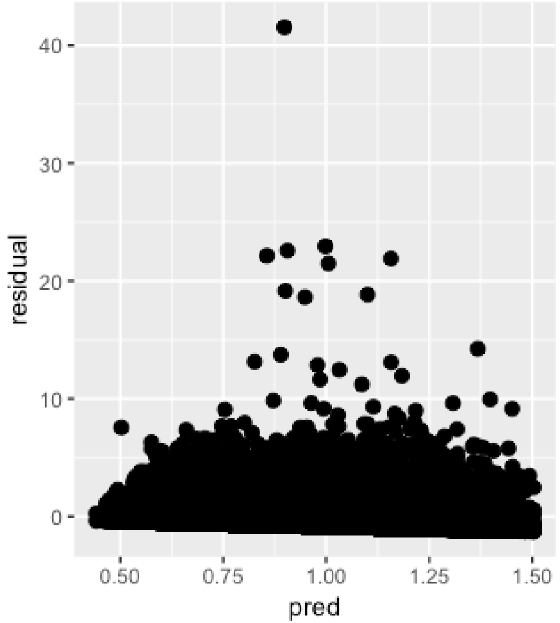
```
Model 1: salesquantity ~ bops_in_effect * bops_user + dummy_homeowner_code +
    dummy_child + age_band + est_income_code + length_of_residence +
    female
Model 2: salesquantity ~ bops_in_effect * bops_user + dummy_homeowner_code +
    dummy_child + age_band + est_income_code + length_of_residence +
    female
  #Df   LogLik Df  Chisq Pr(>Chisq)
1  11 -171095
2  10 -223989 -1 105787  < 2.2e-16 ***
---
Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
```

```
Model 1: salesquantity ~ bops_in_effect * bops_user + dummy_homeowner_
    dummy_child + age_band + est_income_code + length_of_residence +
    female
Model 2: salesquantity ~ 1
  #Df   LogLik Df  Chisq Pr(>Chisq)
1  11 -171095
2   2 -173071 -9 3952.4  < 2.2e-16 ***
```

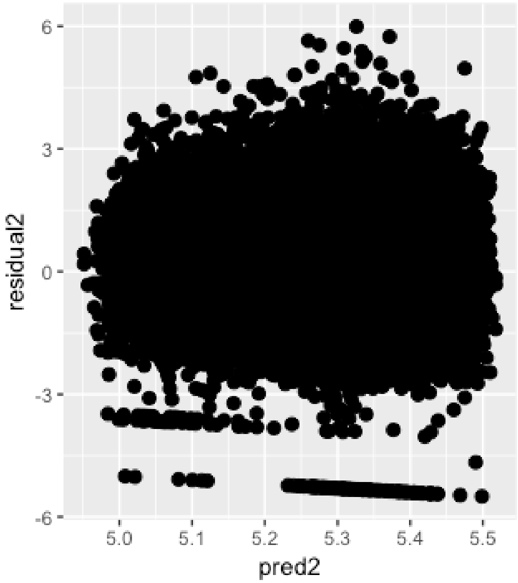
Q3 - Sales Quantity Heteroskedasticity



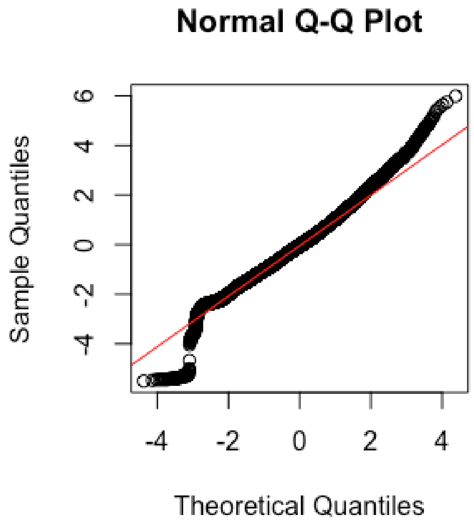

```
> gqtest(model5a)

        Goldfeld-Quandt test

data:  model5a
GQ = 0.1403, df1 = 42200, df2 = 42200, p-value = 1
alternative hypothesis: variance increases from segment 1 to 2

> bptest(model5a) #both tests showed no heteroskedasticity

        studentized Breusch-Pagan test

data:  model5a
```



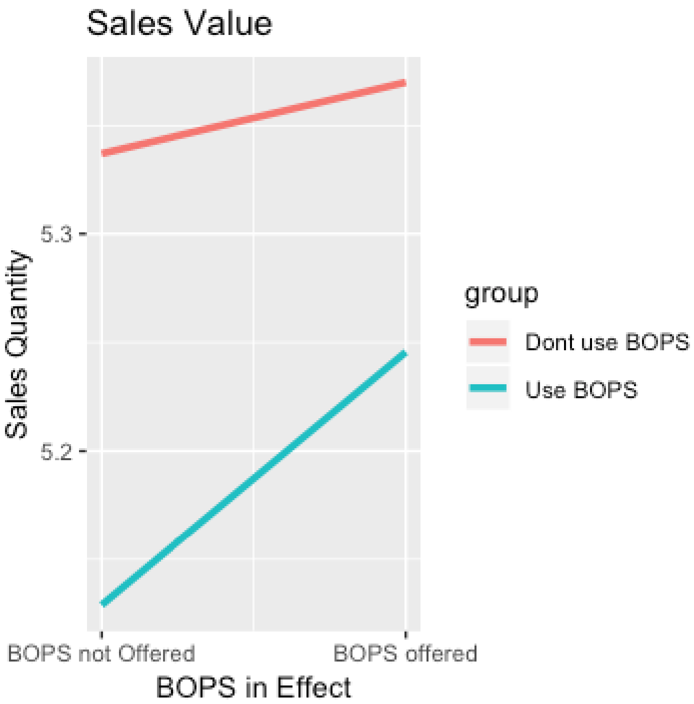
Q3 - Sales Value Heteroskedasticity




```
> gqtest(model6) #showed no heteroskedasticity

        Goldfeld-Quandt test

data:  model6
GQ = 0.87052, df1 = 42200, df2 = 42200, p-value = 1
alternative hypothesis: variance increases from segment 1 to 2

> bptest(model6) #showed heteroskedasticity

        studentized Breusch-Pagan test

data:  model6
BP = 493.98, df = 9, p-value < 2.2e-16
```



Q3 - Marginal Plot



Question 4 - Probit model approach

BOPS coefficient is significant. However, interpreting the coefficient for a probit model is difficult to understand

Regression Results

	Dependent variable: return	
	Normal SE	HW-Robust SE
	(1)	(2)
bops	0.105***	0.105***
	(0.004)	(0.004)
Constant	-2.270***	-2.270***
	(0.021)	(0.018)
Observations	1,170,564	1,170,564
Log Likelihood	-362,820.700	-362,820.700
Akaike Inf. Crit.	725,717.400	725,717.400
Note:	*p<0.05; **p<0.01; ***p<0.001	

Note: Control variables omitted for brevity

[*Link to full model output*]

Question 4 - Comparable to OLS model

To compare OLS and probit models, we first have to **generate the marginal effects** of the probit model *(left column)*.

Since the marginal effects coefficient of BOPS in the probit model **is similar to that of the OLS model**, we can assume that the OLS model is a good estimator as well.

Regression Results

	Dependent variable: return	
	probit Marg Eff w/ RobStdErr	OLS OLS w/ RobStdErr
	(1)	(2)
bops	0.0176***	0.0158***
	(0.0007)	(0.0007)
Observations	1,170,564	1,170,564
R2		0.0279
Adjusted R2		0.0279
Log Likelihood	-362,820.7000	
Akaike Inf. Crit.	725,717.4000	
Residual Std. Error		0.2956
F Statistic		908.3410***
Note:	*p<0.05; **p<0.01; ***p<0.001	

Note: Control variables omitted for brevity

[Link to full model output]()

Question 4 - Addressing endogeneity

Conceptually, the key ind. var. BOPS is a decision variable that is correlated with our dependent variable. Thus, endogeneity is present in our model:

- We address this endogeneity by utilizing **length of residence** as an instrumental variable for BOPS
- Why length of residence as proxy?
  - We believe **the longer a customer has lived at an address, the less likely they are to use BOPS service** (due to familiarity of safety within a neighborhood)

$$Y_{Return} = \beta_0 + \beta_1 BOPS + \sum \beta_i Controls$$

$$X_1 = \gamma_0 + \gamma_1 Length\ of\ Residence + \sum \gamma_j Controls$$

Link to full model output

Question 4 - Summary Statistics

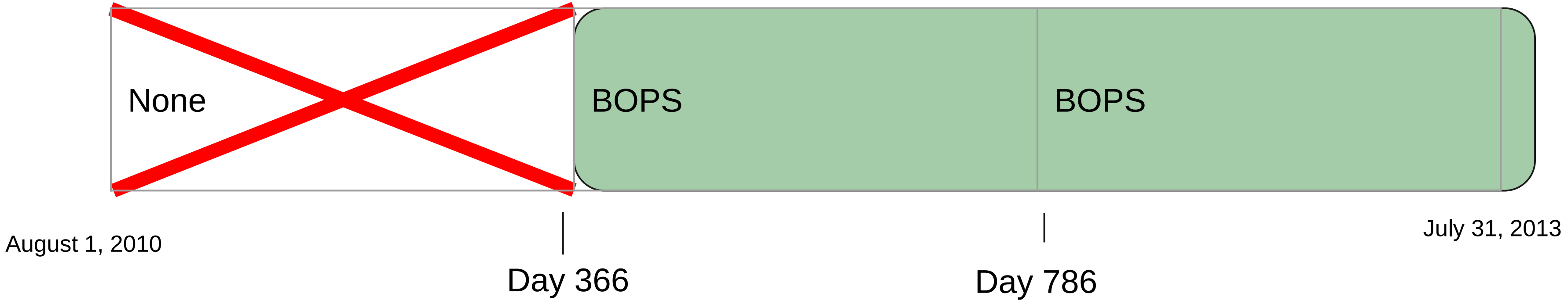
```
  customer_id            purchase_date       transaction_id      store_number         price                 sku
 Min.   :       100348   Length:1170568     Min.   :  50002    Min.   :   2.0    Min.   :    0.00    Min.   :11373024
 1st Qu.:     28454419   Class :character   1st Qu.:3262163    1st Qu.:   2.0    1st Qu.:   44.24    1st Qu.:17951286
 Median :     31964480   Mode  :character   Median :3787321    Median :   2.0    Median :   89.99    Median :18214460
 Mean   : 23247802315                       Mean   :3751126    Mean   : 180.4    Mean   :  170.16    Mean   :18424852
 3rd Qu.:     35423835                      3rd Qu.:4236822    3rd Qu.:   2.0    3rd Qu.:  186.99    3rd Qu.:18697427
 Max.   :919650001519                       Max.   :4702552    Max.   :5998.0    Max.   :39422.00    Max.   :80006100

     return            age_band       est_income_code   homeowner_code      length_of_residence    child
 Min.   :0.00000   Min.   : 0.000   Min.   : 0.000   Length:1170568     Min.   : 0.000       Length:1170568
 1st Qu.:0.00000   1st Qu.: 0.000   1st Qu.: 0.000   Class :character   1st Qu.: 2.000       Class :character
 Median :0.00000   Median : 5.000   Median : 5.000   Mode  :character   Median : 6.000       Mode  :character
 Mean   :0.09983   Mean   : 4.832   Mean   : 4.856                      Mean   : 7.178
 3rd Qu.:0.00000   3rd Qu.: 8.000   3rd Qu.: 8.000                      3rd Qu.:13.000
 Max.   :1.00000   Max.   :13.000   Max.   :13.000                      Max.   :15.000

      year          month            month_index    product_category  month_dummy       week_index         bops
 Min.   :2011   Length:1170568     Min.   :25.00   Min.   : 1.0     Min.   : 1.000   Min.   : 53.0   Min.   :0.0000
 1st Qu.:2012   Class :character   1st Qu.:30.00   1st Qu.: 5.0     1st Qu.: 4.000   1st Qu.: 78.0   1st Qu.:0.0000
 Median :2012   Mode  :character   Median :39.00   Median : 9.0     Median : 8.000   Median :117.0   Median :0.0000
 Mean   :2012                      Mean   :37.03   Mean   :10.1     Mean   : 7.387   Mean   :107.1   Mean   :0.2376
 3rd Qu.:2013                      3rd Qu.:42.00   3rd Qu.:12.0     3rd Qu.:12.000   3rd Qu.:129.0   3rd Qu.:0.0000
 Max.   :2013                      Max.   :48.00   Max.   :21.0     Max.   :12.000   Max.   :157.0   Max.   :1.0000
                                                   NA's   :4
     female          hasChild          ownHome           logprice
 Min.   :0.000   Min.   :0.0000   Min.   :0.0000   Min.   : 0.000
 1st Qu.:0.000   1st Qu.:0.0000   1st Qu.:0.0000   1st Qu.: 3.812
 Median :0.490   Median :0.0000   Median :1.0000   Median : 4.511
 Mean   :0.488   Mean   :0.4019   Mean   :0.6644   Mean   : 4.466
 3rd Qu.:1.000   3rd Qu.:1.0000   3rd Qu.:1.0000   3rd Qu.: 5.236
 Max.   :1.000   Max.   :1.0000   Max.   :1.0000   Max.   :10.582
```

Notes on data clean-up:

- **Data was subset** to only include data points when **bops was implemented**.
- Missing data points were replaced with sample mean (e.g. *age_band*, *length_of_residence*, *female*), except for "Product Category" variable.
- "hasChild" is dummy variable for "child".
- "ownHome" is dummy variable for "homeowner_code".
- "Logprice" created as "price" variable was right-skewed.

Question 4 - Standardization of Time

Since we are concerned with the effect of BOPS on return, we will exclude all data points when BOPS was not implemented (i.e. BOPS = n/a):



Question 4 - Full Probit Output

Regression Results

	Dependent variable:	
	return	
	Normal SE	HW-Robust SE
	(1)	(2)
bops	0.105*** (0.004)	0.105*** (0.004)
logprice	0.223*** (0.003)	0.223*** (0.002)
factor(store_number)6	-0.034*** (0.007)	-0.034*** (0.007)
factor(store_number)5998	-0.184*** (0.011)	-0.184*** (0.010)
factor(month_dummy)2	-0.130*** (0.007)	-0.130*** (0.007)
factor(month_dummy)3	-0.063*** (0.008)	-0.063*** (0.009)
factor(month_dummy)4	-0.117*** (0.009)	-0.117*** (0.009)
factor(month_dummy)5	-0.164*** (0.008)	-0.164*** (0.008)
factor(month_dummy)6	-0.100*** (0.009)	-0.100*** (0.009)
factor(month_dummy)7	-0.133*** (0.009)	-0.133*** (0.009)
factor(month_dummy)8	-0.095*** (0.010)	-0.095*** (0.010)
factor(month_dummy)9	-0.117*** (0.010)	-0.117*** (0.010)
factor(month_dummy)10	-0.094*** (0.009)	-0.094*** (0.009)
factor(month_dummy)11	-0.135*** (0.008)	-0.135*** (0.008)
factor(month_dummy)12	-0.179*** (0.007)	-0.179*** (0.007)
factor(year)2012	-0.046*** (0.005)	-0.046*** (0.005)
factor(year)2013	-0.067*** (0.007)	-0.067*** (0.007)
factor(product_category)2	0.348*** (0.011)	0.348*** (0.012)
factor(product_category)3	-0.040** (0.012)	-0.040** (0.015)
factor(product_category)4	0.032*** (0.009)	0.032** (0.010)
factor(product_category)5	-0.025** (0.010)	-0.025* (0.011)
factor(product_category)14	0.179*** (0.020)	0.179*** (0.020)
factor(product_category)15	-2.393 (25.607)	-2.393*** (0.147)
factor(product_category)17	-0.186*** (0.027)	-0.186*** (0.032)
factor(product_category)20	0.219*** (0.011)	0.219*** (0.013)
factor(product_category)21	0.009 (0.010)	0.009 (0.011)
age_band	-0.003*** (0.0004)	-0.003*** (0.0004)
female	0.169*** (0.004)	0.169*** (0.004)
hasChild	0.014*** (0.003)	0.014*** (0.003)
Constant	-2.270*** (0.021)	-2.270*** (0.018)
Observations	1,170,564	1,170,564
Log Likelihood	-362,820.700	-362,820.700
Akaike Inf. Crit.	725,717.400	725,717.400
Note:	*p<0.05; **p<0.01; ***p<0.001	

Question 4 - Likelihood Ratio Test & Predictive Power

```
Likelihood ratio test

Model 1: return ~ bops + factor(store_number) + logprice + age_band +
    female + hasChild
Model 2: return ~ 1
  #Df  LogLik Df Chisq Pr(>Chisq)
1   8 -365500
2   1 -380104 -7 29208  < 2.2e-16 ***
---
Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
```

To test model fit, a new probit model with fewer control variables was created (Model 1) and compared to a null model:

- The test is significant, indicating that the model with variables beats the null model.
- We can conclude that our initial model (with more variables) fits the data.

```
> print(paste('Accuracy', 1 - misClasificError))  # Accuracy = 90.02% - Damn good.
[1] "Accuracy 0.900165560650898"
```

This model has a very good predictive power

Question 4 - Full OLS v Probit

Regression Results

Dependent variable: return

	probit Marg Eff w/ RobStdErr (1)	OLS OLS w/ RobStdErr (2)
bops	0.0176***	0.0158***
	(0.0007)	(0.0007)
logprice	0.0359***	0.0292***
	(0.0003)	(0.0002)
factor(store_number)6	-0.0054***	-0.0052***
	(0.0011)	(0.0011)
factor(store_number)5998	-0.0264***	-0.0290***
	(0.0013)	(0.0015)
factor(month_dummy)2	-0.0196***	-0.0285***
	(0.0010)	(0.0013)
factor(month_dummy)3	-0.0097***	-0.0151***
	(0.0013)	(0.0017)
factor(month_dummy)4	-0.0176***	-0.0184***
	(0.0012)	(0.0015)
factor(month_dummy)5	-0.0241***	-0.0327***
	(0.0010)	(0.0014)
factor(month_dummy)7	-0.0197***	-0.0287***
	(0.0013)	(0.0017)
factor(month_dummy)8	-0.0144***	-0.0205***
	(0.0014)	(0.0018)
factor(month_dummy)9	-0.0176***	-0.0241***
	(0.0014)	(0.0019)
factor(month_dummy)10	-0.0143***	-0.0178***
	(0.0014)	(0.0017)
factor(month_dummy)11	-0.0203***	-0.0283***
	(0.0011)	(0.0015)
factor(month_dummy)12	-0.0272***	-0.0359***
	(0.0011)	(0.0013)
factor(year)2012	-0.0075***	-0.0078***
	(0.0008)	(0.0008)
factor(year)2013	-0.0106***	-0.0093***
	(0.0010)	(0.0012)
factor(product_category)2	0.0689***	0.0411***
	(0.0028)	(0.0030)
factor(product_category)3	-0.0063**	-0.0109**
	(0.0022)	(0.0038)
factor(product_category)4	0.0052**	-0.0193***
	(0.0017)	(0.0025)
factor(product_category)5	-0.0041*	-0.0340***
	(0.0017)	(0.0025)
factor(product_category)14	0.0325***	-0.0037
	(0.0041)	(0.0041)
factor(product_category)15	-0.0891***	-0.1732***
	(0.0003)	(0.0092)
factor(product_category)17	-0.0264***	-0.0246**
	(0.0040)	(0.0085)
factor(product_category)20	0.0404***	0.0405***
	(0.0027)	(0.0035)
factor(product_category)21	0.0015	-0.0353***
	(0.0017)	(0.0025)
age_band	-0.0005***	-0.0004***
	(0.0001)	(0.0001)
female	0.0272***	0.0274***
	(0.0006)	(0.0006)
hasChild	0.0022***	0.0021***
	(0.0005)	(0.0006)
Observations	1,170,564	1,170,564
R2		0.0279
Adjusted R2		0.0279
Log Likelihood	-362,820.7000	
Akaike Inf. Crit.	725,717.4000	
Residual Std. Error		0.2956
F Statistic		908.3410***

Note: *p<0.05; **p<0.01; ***p<0.001

Question 4 - IV Reg Diagnostics

Using length of residence as an instrument variable. Note:

- Sargan test unavailable since only one instrument used
- F-statistic of 163 > 10 - the instrument in use is relevant
- Significant Hausman test, so we will interpret the IVReg/2SLS model estimation

```
Diagnostic tests:
                     df1     df2 statistic p-value
Weak instruments       1 1170526   163.533 < 2e-16 ***
Wu-Hausman             1 1170525     9.816 0.00173 **
Sargan                 0      NA        NA      NA
---
Signif. codes:  0 ‘***’ 0.001 ‘**’ 0.01 ‘*’ 0.05 ‘.’ 0.1 ‘ ’ 1

Residual standard error: 0.3043 on 1170526 degrees of freedom
Multiple R-Squared: -0.03044,   Adjusted R-squared: -0.03047
Wald test: 842.4 on 37 and 1170526 DF,  p-value: < 2.2e-16
```

Question 4 - Full IV Reg Output

Regression Results

	Dependent variable: return	
	Normal SE	HW-Robust SE
	(1)	(2)
bops	0.1892***	0.1892***
	(0.0570)	(0.0569)
logprice	0.0290***	0.0290***
	(0.0003)	(0.0003)
factor(store_number)6	0.0115*	0.0115*
	(0.0056)	(0.0056)
factor(store_number)5998	-0.0578***	-0.0578***
	(0.0096)	(0.0096)
factor(month_dummy)2	-0.0314***	-0.0314***
	(0.0016)	(0.0017)
factor(month_dummy)3	-0.0201***	-0.0201***
	(0.0023)	(0.0024)
factor(month_dummy)4	-0.0205***	-0.0205***
	(0.0016)	(0.0017)
factor(month_dummy)5	-0.0344***	-0.0344***
	(0.0015)	(0.0015)
factor(month_dummy)6	-0.0273***	-0.0273***
	(0.0023)	(0.0024)
factor(month_dummy)7	-0.0350***	-0.0350***
	(0.0026)	(0.0027)
factor(month_dummy)8	-0.0162***	-0.0162***
	(0.0023)	(0.0024)
factor(month_dummy)9	-0.0331***	-0.0331***
	(0.0035)	(0.0035)
factor(month_dummy)10	-0.0245***	-0.0245***
	(0.0028)	(0.0028)
factor(month_dummy)11	-0.0412***	-0.0412***
	(0.0045)	(0.0045)
factor(month_dummy)12	-0.0479***	-0.0479***
	(0.0041)	(0.0042)
factor(year)2012	-0.0284***	-0.0284***
	(0.0068)	(0.0068)
factor(year)2013	-0.0326***	-0.0326***
	(0.0078)	(0.0078)
factor(product_category)2	0.0408***	0.0408***
	(0.0024)	(0.0031)
factor(product_category)3	-0.0067*	-0.0067
	(0.0033)	(0.0041)
factor(product_category)4	-0.0059	-0.0059
	(0.0048)	(0.0051)
factor(product_category)15	-0.1453	-0.1453***
	(0.1524)	(0.0139)
factor(product_category)17	-0.0400***	-0.0400***
	(0.0083)	(0.0101)
factor(product_category)20	0.0513***	0.0513***
	(0.0045)	(0.0050)
factor(product_category)21	-0.0283***	-0.0283***
	(0.0031)	(0.0034)
age_band	0.0001	0.0001
	(0.0002)	(0.0002)
female	0.0230***	0.0230***
	(0.0016)	(0.0016)
hasChild	0.0014*	0.0014*
	(0.0006)	(0.0006)
Constant	-0.0094	-0.0094
	(0.0083)	(0.0084)
Observations	1,170,564	1,170,564
R2	-0.0304	-0.0304
Adjusted R2	-0.0305	-0.0305
Residual Std. Error	0.3043	0.3043
Note:	*p<0.05; **p<0.01; ***p<0.001	

Question 5 - Heteroskedasticity

Sales Value

```
> gqtest(salesval) #No Heteroskedasticity

        Goldfeld-Quandt test

data:  salesval
GQ = 0.464, df1 = 10491, df2 = 10490, p-value = 1
alternative hypothesis: variance increases from segment 1 to 2

> bptest(salesval) #Heteroskedasticity

        studentized Breusch-Pagan test

data:  salesval
BP = 945.55, df = 10, p-value < 2.2e-16
```

```
> gqtest(salesquantnb) #No heteroskedasticity

        Goldfeld-Quandt test

data:  salesquantnb
GQ = 0.0077548, df1 = 10491, df2 = 10490, p-value = 1
alternative hypothesis: variance increases from segment 1 to 2

> bptest(salesquantnb) #Heteroskedasticity

        studentized Breusch-Pagan test

data:  salesquantnb
BP = 79.827, df = 10, p-value = 0.0000000000005428
```

Return Value

```
> gqtest(returnval)#No heteroskedasticity

        Goldfeld-Quandt test

data:  returnval
GQ = 0.81164, df1 = 10490, df2 = 10489, p-value = 1
alternative hypothesis: variance increases from segment 1 to 2

> bptest(returnval) #Heteroskedastic

        studentized Breusch-Pagan test

data:  returnval
BP = 3181.5, df = 11, p-value < 2.2e-16
```

```
> gqtest(returnquantnb) #No heteroskedasticity

        Goldfeld-Quandt test

data:  returnquantnb
GQ = 0.019753, df1 = 10490, df2 = 10489, p-value = 1
alternative hypothesis: variance increases from segment 1 to 2

> bptest(returnquantnb) #No heteroskedastic

        studentized Breusch-Pagan test

data:  returnquantnb
BP = 848.96, df = 11, p-value < 2.2e-16
```

Question 5 - Choosing Negative Binomial

Sales Quantity

```
> lrtest(salesquant, salesquant1) #LR Test is significant. The Poisson model does not fit data.
Likelihood ratio test

Model 1: salesquantity ~ final_day * storegroup + product_category + avg_female +
    avg_age + avg_income + avg_homeowner + avg_residency + avg_childowner
Model 2: salesquantity ~ 1
  #Df   LogLik  Df  Chisq Pr(>Chisq)
1  11 -1340274
2   1 -1520165 -10 359782  < 2.2e-16 ***
---
Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
> #Assess model fit for our negative binomial model.
> lrtest(salesquantnb, salesquantnb1)
Likelihood ratio test

Model 1: salesquantity ~ final_day * storegroup + product_category + avg_female +
    avg_age + avg_income + avg_homeowner + avg_residency + avg_childowner
Model 2: salesquantity ~ 1
  #Df LogLik  Df  Chisq Pr(>Chisq)
1  12 -92659
2   2 -95591 -10 5864.7  < 2.2e-16 ***
---
Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
> #Compare poisson and NB models to choose a model.
> lrtest(salesquant, salesquantnb)#P value is significant, we will use negative binomial as our final model to assess sales quantity.
Likelihood ratio test

Model 1: salesquantity ~ final_day * storegroup + product_category + avg_female +
    avg_age + avg_income + avg_homeowner + avg_residency + avg_childowner
Model 2: salesquantity ~ final_day * storegroup + product_category + avg_female +
    avg_age + avg_income + avg_homeowner + avg_residency + avg_childowner
  #Df   LogLik Df   Chisq Pr(>Chisq)
1  11 -1340274
2  12   -92659  1 2495231  < 2.2e-16 ***
---
Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
```

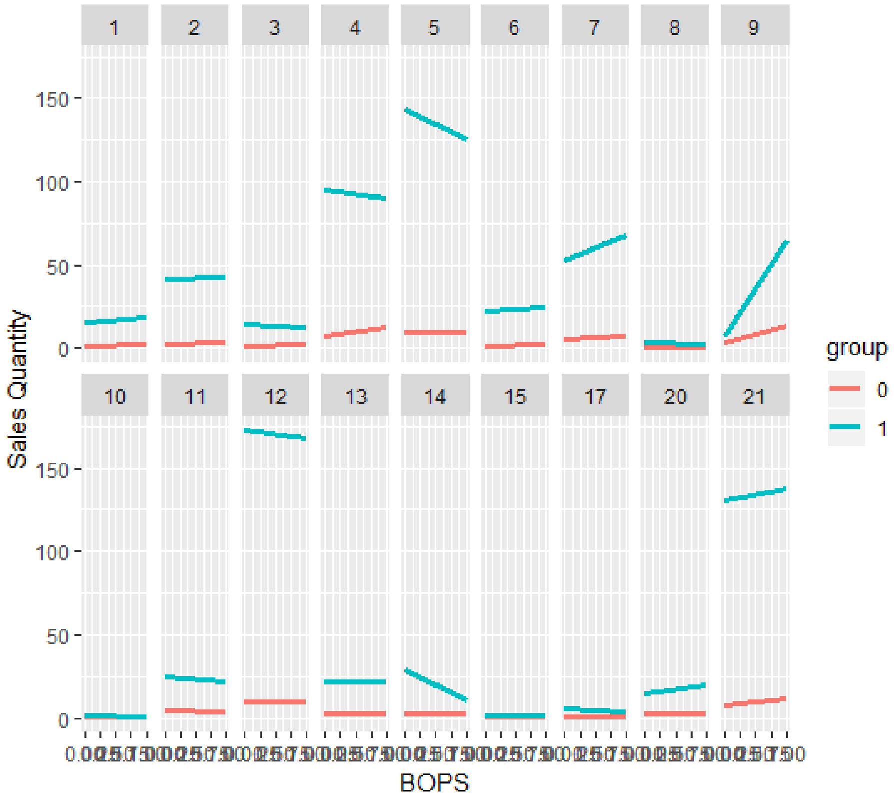
Return Quantity

```
> lrtest(returnquant, returnquant1) #LR Test is significant. The Poisson model does not fit data.
Likelihood ratio test

Model 1: returnquantity ~ final_day * storegroup + product_category +
    avg_female + avg_age + avg_income + avg_homeowner + avg_residency +
    avg_childowner + salesquantity
Model 2: returnquantity ~ 1
  #Df  LogLik  Df  Chisq Pr(>Chisq)
1  12 -110580
2   1 -165219 -11 109276  < 2.2e-16 ***
---
Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
> #Assess model fit for our negative binomial model.
> lrtest(returnquantnb, returnquantnb1)
Likelihood ratio test

Model 1: returnquantity ~ final_day * storegroup + product_category +
    avg_female + avg_age + avg_income + avg_homeowner + avg_residency +
    avg_childowner + salesquantity
Model 2: returnquantity ~ 1
  #Df LogLik  Df Chisq Pr(>Chisq)
1  13 -44006
2   2 -50916 -11 13820  < 2.2e-16 ***
---
Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
> #Compare poisson and NB models to choose a model.
> lrtest(returnquant, returnquantnb)#P value is significant, we will use negative binomial as our final model to assess sales quantity.
Likelihood ratio test

Model 1: returnquantity ~ final_day * storegroup + product_category +
    avg_female + avg_age + avg_income + avg_homeowner + avg_residency +
    avg_childowner + salesquantity
Model 2: returnquantity ~ final_day * storegroup + product_category +
    avg_female + avg_age + avg_income + avg_homeowner + avg_residency +
    avg_childowner + salesquantity
  #Df  LogLik Df  Chisq Pr(>Chisq)
1  12 -110580
2  13  -44006  1 133149  < 2.2e-16 ***
---
Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
```

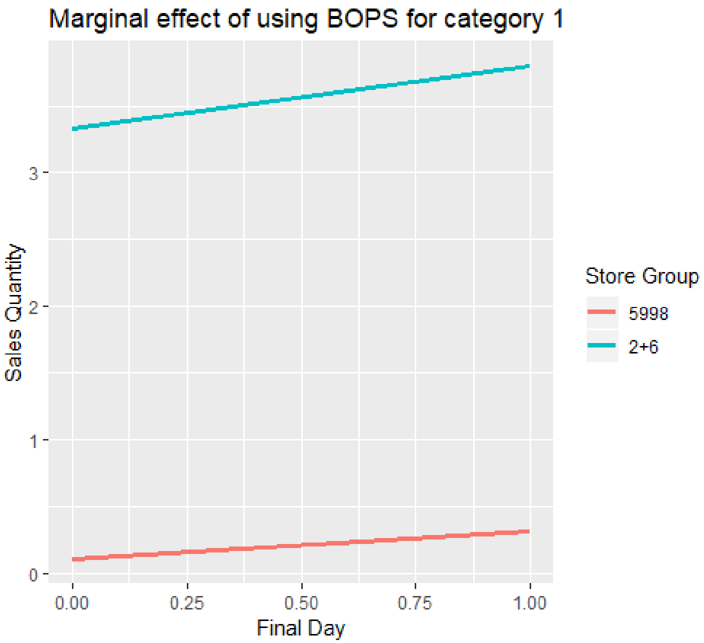
Q6 - Sales Quantity

The marginal effect plots for all product categories

*We found that **4 out of the 21** categories have a significant difference*



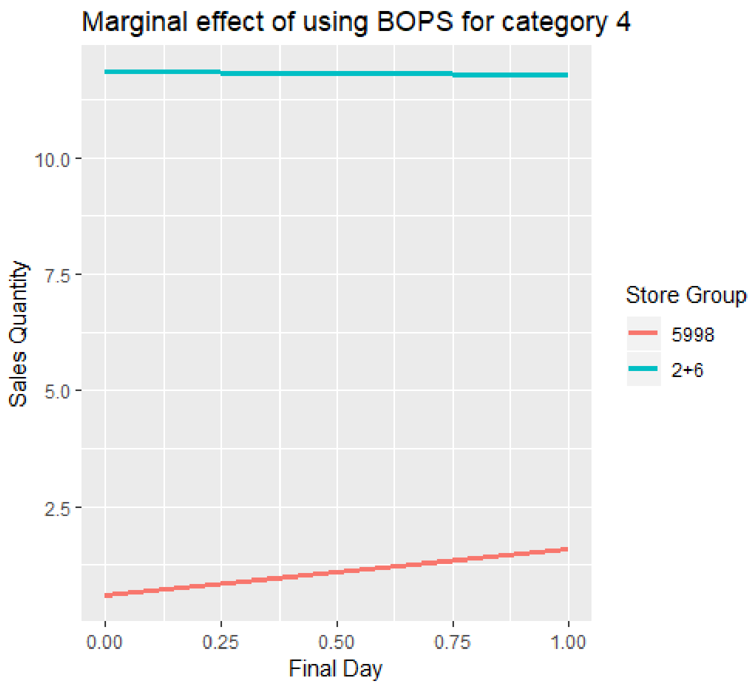
Sales Quantity- Product Category 1



Category 1

	Dependent variable:
	returnquantity Sales Quantity
final_day	1.05*
	(0.42)
storegroup	3.40***
	(0.39)
avg_female	0.21
	(0.15)
avg_age	-0.11***
	(0.02)
avg_income	0.19***
	(0.03)
avg_homeowner	-0.69***
	(0.17)
avg_residency	-0.02
	(0.01)
avg_childowner	0.33*
	(0.16)
final_day:storegroup	-0.92*
	(0.43)
Constant	-2.26***
	(0.44)
Observations	1,381
Log Likelihood	-2,892.23
theta	0.64*** (0.04)
Akaike Inf. Crit.	5,804.46
Note:	*p<0.05; **p<0.01; ***p<0.001

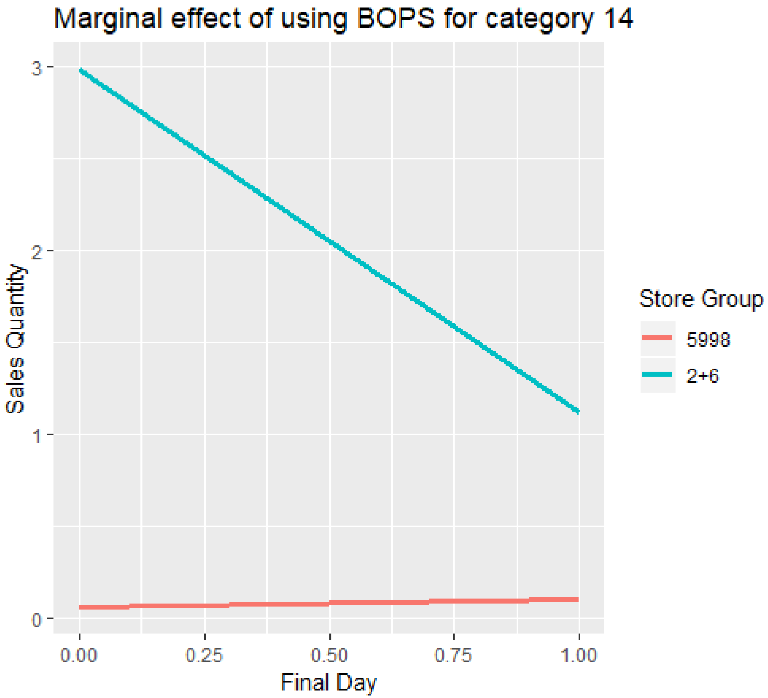
Sales Quantity- Product Category 4



Category 4

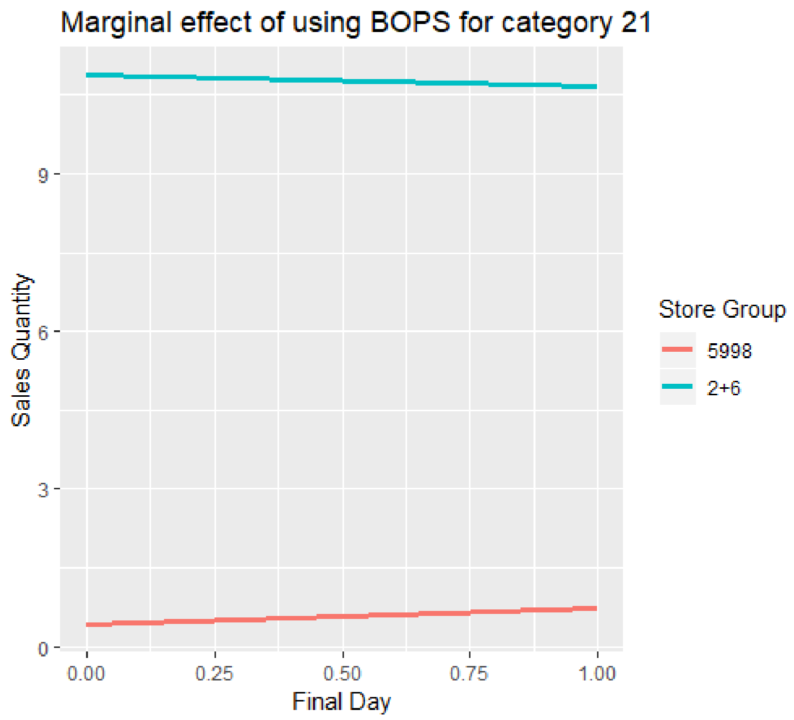
	Dependent variable: returnquantity Sales Quantity
final_day	0.98*** (0.18)
storegroup	2.98*** (0.16)
avg_female	-2.87*** (0.19)
avg_age	-0.07** (0.03)
avg_income	0.36*** (0.05)
avg_homeowner	-1.66*** (0.25)
avg_residency	-0.09*** (0.02)
avg_childowner	-0.68** (0.23)
final_day:storegroup	-0.99*** (0.19)
Constant	1.15*** (0.31)
Observations	1,838
Log Likelihood	-5,383.05
theta	0.52*** (0.02)
Akaike Inf. Crit.	10,786.10
Note:	*p<0.05; **p<0.01; ***p<0.001

Sales Quantity-
Product Category 14




```
Category 14
==================================================
                     Dependent variable:
                 ---------------------------
                       returnquantity
                       Sales Quantity
--------------------------------------------------
final_day                   0.53
                           (0.68)

storegroup                  3.88***
                           (0.54)

avg_female                 -0.20
                           (0.18)

avg_age                    -0.09***
                           (0.02)

avg_income                  0.05
                           (0.04)

avg_homeowner              -0.08
                           (0.21)

avg_residency              -0.03
                           (0.02)

avg_childowner             -0.24
                           (0.18)

final_day:storegroup       -1.50*
                           (0.69)

Constant                   -2.09***
                           (0.59)

--------------------------------------------------
Observations                1,079
Log Likelihood            -1,763.42
theta                   0.49*** (0.04)
Akaike Inf. Crit.          3,546.84
==================================================
Note:              *p<0.05; **p<0.01; ***p<0.001
```

Sales Quantity-Product Category 21



Category 21

	Dependent variable: returnquantity Sales Quantity
final_day	0.532***
	(0.187)
storegroup	3.248***
	(0.166)
avg_female	-2.855***
	(0.201)
avg_age	-0.250***
	(0.027)
avg_income	0.359***
	(0.052)
avg_homeowner	0.287
	(0.280)
avg_residency	-0.031
	(0.022)
avg_childowner	-0.667***
	(0.238)
final_day:storegroup	-0.552***
	(0.204)
Constant	0.279
	(0.346)
Observations	1,835
Log Likelihood	-5,033.139
theta	0.500*** (0.020)
Akaike Inf. Crit.	10,086.280
Note:	*p<0.1; **p<0.05; ***p<0.01