Abstract

This report analyses aggregate level data for the fragrance market in Italy. The primary objectives of this research are as follows:

a) Assess the Price Sensitivity of Each Focal Brand
b) Assess the Communication Impact for Each of the Focal Brands
c) Assess the Competitive Effects
d) Advice on Budget Allocation and Optimisation for the Rest of the Year 2017.

This research uses regression models created using Ordinary Least Squares (OLS) as well as Instrumental Variables (IV). IV is used to overcome the issue of reverse causality which causes an endogeneity problem in identifying the impact of the communication variables as well as the price sensitivity of the focal brands.

This study finds that the focal fragrance brands could reduce their prices near their main selling period to realise higher revenue. Further, fragrances sold in bundles can still face competitive effects due to communication spend done by competing fragrances sold in the same package.

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1 Introduction

This report uses 129 observations of some of the firms in the fragrance market in Italy to analyse the following research questions:

a) Assess the Price Sensitivity of Each "Focal" Brand
b) Assess the Communication Impact for Each of the Focal Brands
c) Assess the Competitive Effects
d) Advice on Budget Allocation and Optimisation for the Rest of the Year 2017

1.1 The scope of Econometric Analysis

IV along with OLS were applied for econometric analysis. IV has been used to overcome the issue of reverse causality which caused an endogeneity problem making identification of the price sensitivity and communication impact difficult. The graphs shown below illustrates this issue. We can see this for c1 Si; communication investment is high in periods of high sales quantity which raises a question of the direction of causality between communication expenditure and sales quantity. This pattern is observed for all the focal brands (for more information, please refer to Appendix B).

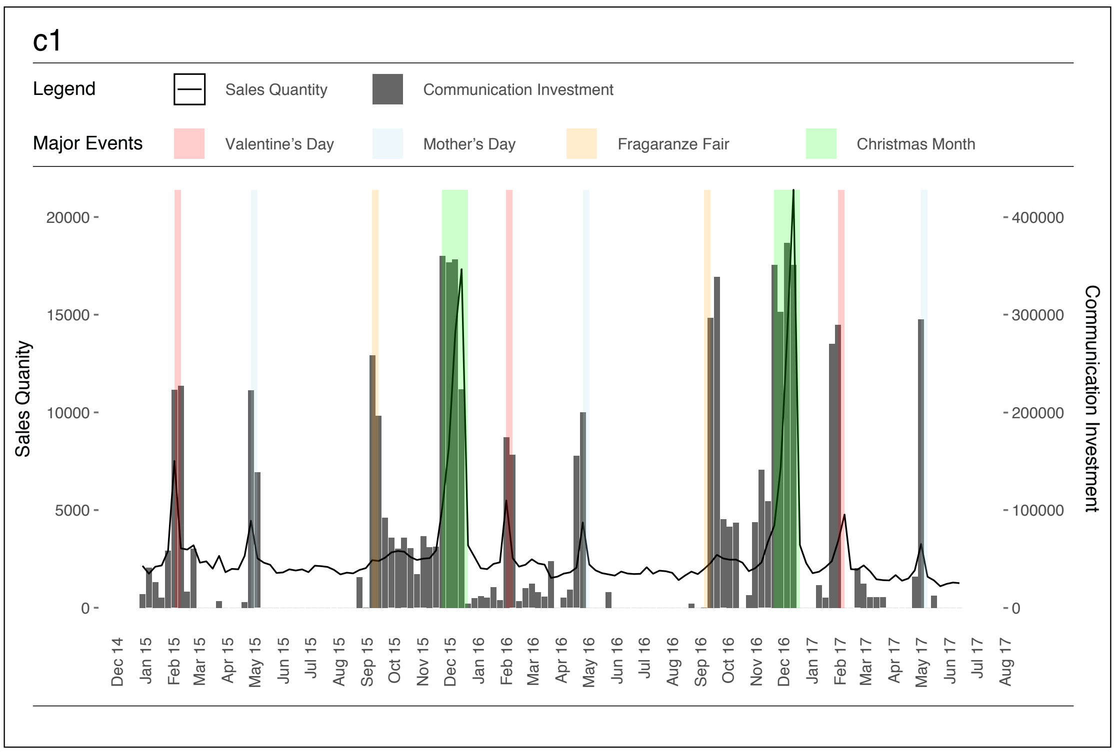

Figure 1: c1 Si Sales Quanity and Communication Investment along with Major Perfume Selling Periods in Italy

Instrumental Variables

Throughout this report, two instruments are used for communication expenditure of the respective focal brands.

a) Google trend data for the brand names of the fragrances. For instance, google trend data of "c1" was used as an instrument for the advertising expenditure on c1 Si.

b) "non_com_high_in" - a dummy variable indicating periods of moderate and high investments (> 299880) by non-competitors. Investment by non-competitors was calculated as shown below. Moreover, the histogram below shows there are only a few occasions when the investment for non-competitors is below the level indicated. This observation is the reason why the dummy variable uses this value to indicate periods of moderate and high investment. Other measures including the mean and median could have also been used. They give out similar results.

$$\text{Non Competitor Investment} = \text{Total Market Investment} - \text{Investment by Focal Brands}$$

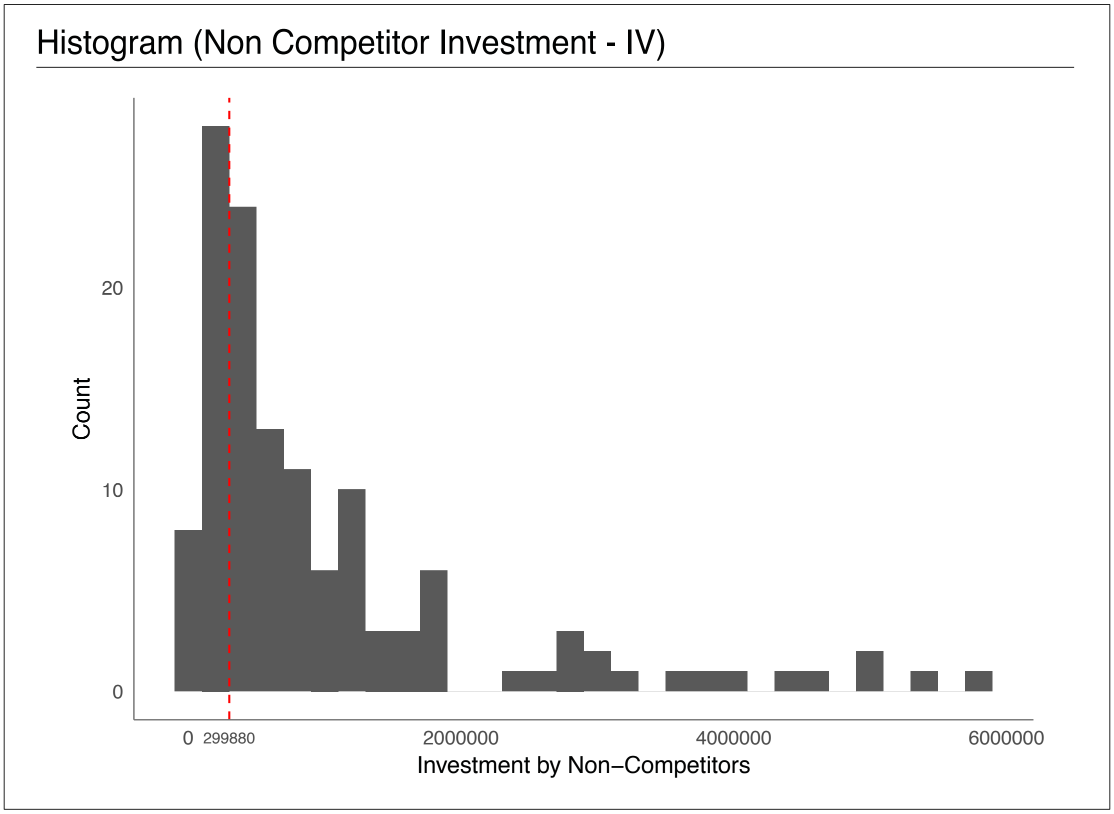

Figure 2: A Histogram Showing Cut-off used to create the IV variable

Both of these two variables are likely to be correlated to the communication expenditure of each focal brand, and therefore is expected to satisfy the instrument relevance condition (Wooldridge 2013). To evaluate the validity of these instrument variables the following three diagnostic tests were used:

a) Weak Instrument Test - This is an F-test on the instruments in the first stage. The null hypothesis is that instruments are weak (not relevant), so a rejection means that the instrument relevance condition is satisfied.

b) Wu-Hausman Test - This tests the consistency of the OLS estimates under the assumption that the IV is consistent. When we reject, it means OLS is not consistent, suggesting endogeneity is present.

c) Sargan Test - This is a test of instrument exogeneity using overidentifying restrictions, called the J-statistic in Stock and Watson. If the null is rejected, at least one of our instruments is invalid (Sundstrom 2016).

1.2 Dataset

Google trend data was added for the following keywords to create IV variables and control for the high seasonality in the dataset.

Table 1: Google Trend Data

Keyword	Purpose
profumo	Seasonality and Trend
c1_profumo	IV
c2_profumo	IV
c3_profumo	IV
c1_si	Seasonality and Trend
c2_black_opium	Seasonality and Trend
c3_la_vie_est_belle	Seasonality and Trend
c1	IV
c2	IV
c3	IV

The following filters were used to get the google trend data. These filters were applied to make the additional data as relevant to this dataset as possible.

Table 2: Google Trend Data Filter

Region	Start Date (yyyy/mm/dd)	End Date (yyyy/mm/dd)	Category
Italy	2015-01-04	2017-06-18	Beauty & Fitness

Apart from the google trend data, the following variables were created to test out various hypothesis.

Table 3: Additional Variables Added to the Dataset

Variable	Purpose
main_selling_period	Controlling for Christmas, Mother's Day, Valentine's and Frangraze Fair
lag_volume_c1_si	Control Variable - Time Series
lag_volume_c2_black_opium	Control Variable - Time Series
lag_volume_c3_la_vie_est_belle	Control Variable - Time Series
investment_non_competitors	IV
non_com_high_in	IV
value_focal	To Compute Competitive Effects
ar.mrkt.share	To Compute Competitive Effects
c2.mrkt.share	To Compute Competitive Effects
lan.mrkt.share	To Compute Competitive Effects
ar.mrkt.share.lag	Control Variable - Time Series
c2.mrkt.share.lag	Control Variable - Time Series
lan.mrkt.share.lag	Control Variable - Time Series

1.3 Limitations and Further Research

The primary limitation of this dataset is that there is incomplete information for firms that are not considered as "focal". Because of variability in the number of observations available for different firms, this research was only able to analyse the three focal brands. Another limitation of this data is the limited sample size. The limited sample size restricts the number of variables that can be entered in the regression equation. Due to this restriction, the subset selection method uses Bayesian Information Criterion (BIC) as it's information criterion since it penalises model complexity more than AIC. For some models, however, Adjusted R-square was used to avoid removing the variable of interest from the regression equation.

Further research can make use of Vector autoregression models to identify and solve the primary objectives of this research. This report avoids using them due to its restricted scope.

2 Analysis

2.1 Price Sensitivity of Each "Focal" Brand

Before beginning the analysis, the stationarity of volume time series for each of the three "focal brand" was evaluated. The results of the tests are shown below:

Table 4: Stationarity Test Results (P-Value) for Sales Quantity

Fragrance	ADF*	PP†	KPSS‡	Conclusion
c1 Si	0.0100000	0.01	0.1	Stationary
c2 Black Opium	0.0664720	0.01	0.1	Stationary
c3 La Vie Est Belle	0.0161853	0.01	0.1	Stationary
Null Hypothesis * Unit Root; † Unit Root; ‡ Stationary;				

The results show that using a lag variable of these series won't be problematic since all three series are stationary.

The analysis of price sensitivity is divided into two sections: Own Price Elasticity and Cross Price Elasticity. This division was made to test the various hypothesis without losing a lot of degrees of freedom.

2.1.1 Own Price Elasticity (OPE)

The regression models for this section can be found in Appendix A. The main result, i.e. the OPE has been summarised in the table below:

Table 5: Own Price Elasticity Summary

	OLS		IV	
Fragrance	OPE	Peak Period OPE	OPE	Peak Period OPE
c1 Si	-1.68	0.00	-1.74	0.00
c2 Black Opium	-3.97	0.00	-4.04	0.00
c3 La Vie Est Belle	-1.54	-3.94	0.00	-3.89

We can observe from this that all three fragrances have elasticities that can be classified as elastic. In regular periods, c2 had the most elastic OPE compared to the other two fragrances. However, this was not the case in peak periods as c3 had the most elastic OPE which was significantly different from c3's OPE in regular periods.

Before moving on to the IV results, the table below shows the results of the diagnostic test conducted to access the validity of using IV. The table shows that both instruments satisfy the relevance condition and there is indeed an issue of endogeneity in case of c1 and c2. The Saragan Test is also satisfactory here.

Table 6: IV Regression Model's Diagnostics (P-Value) for OPE

Fragrance	Weak Instrument Test*	Wu-Hausman Test†	Sargan Test‡
c1 Si	0.0000929	0.0180339	0.4848831
c2 Black Opium	0.0034745	0.0158571	0.2444895
c3 La Vie Est Belle	0.0005563	0.2456917	0.6214017
Null Hypothesis * Instruments not Relevant; † OLS is consistent; ‡ Instruments are valid;			

The results were somewhat similar in regression models which used OLS. A major change was that c3's OPE was not statistically different from zero which suggest that c3's customers were not responsive to the price changes of c3's fragrance in regular periods. This finding needs to be evaluated with caution as this can be caused by the limited sample size of the dataset.

2.1.2 Cross Price Elasticity (CPE)

In this section, various functional forms and regression models were computed to obtain valid estimates of the CPE which have sensible "face" value. The elasticity matrix below shows the main findings from the regression models (for more information, please refer to Appendix A Table 22: OLS (Cross Price Elasticity)).

Table 7: Cross Price Elasticity Matrix

	c1	c2	c3
c1	-7.663270	0.000000	0.1219126
c2	2.335838	-4.822907	0.0000000
c3	0.000000	0.000000	-0.4409626

It is interesting to note that c1's and c2's OPE is increased and has become more elastic. On the other hand, c3's OPE is inelastic in this more complex model.

The Clout and Vulnerability Map below shows the competitive structure of the Italian fragrance market. Here the size of the bubble is encoded to the relative sales of the three fragrances. This graph shows the relative strength of the "c1" brand.

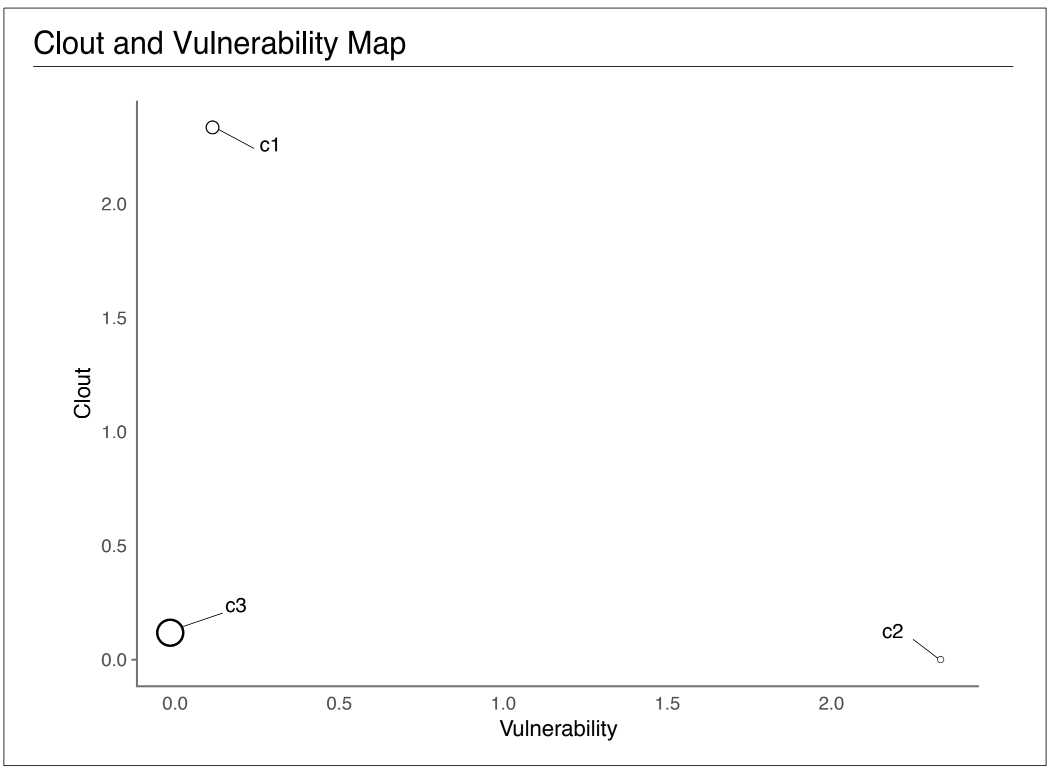

Figure 3: Clout and Vulnerability Map for c1, c2 and c3

Coming over to IV, the diagnostic test show that the IV models are not suitable for the analysis. Also, the Wu-Hausman indicate that OLS is consistent. Therefore IV results are not used for this section.

Table 8: IV Regression Model's Diagnostics (P-Value) for CPE

Fragrance	Weak Instrument Test*	Wu-Hausman Test†	Sargan Test‡
c1 Si	0.0022314	0.5445726	0.0215259
c2 Black Opium	0.0081430	0.8182781	0.9064305
c3 La Vie Est Belle	0.0037548	0.1507992	0.9088021
Null Hypothesis * Instruments not Relevant; † OLS is consistent; ‡ Instruments are valid;			

2.2 Communication Impact for Each of the Focal Brands

This section separates the analyses into Own Communication Impact and Cross Communication Impact.

2.2.1 Own Communication Impact

The condensed regression output below shows that the return from communication expenditure for c1 and c3 follows a diminishing pattern (evident from the negative and significant impact of Investment Sqr variables) (for more information, please refer to Appendix A Table 23: OLS (Own Communication Impact)). Further, the return from c2's investment is higher in main selling periods (almost significant at 10% level when using normal standard errors).

Table 9: OLS (Own Communication Impact) Condensed

	Dependent variable:		
	L c1 Sales Quanitity	L c2 Sales Quanitity	L c3 Sales Quanitity
	(1)	(2)	(3)
Investment c2 in 10000s		0.029** (0.012)	
Investment c3 in 10000s			0.013*** (0.004)
Investment c1 in 10000s	0.026*** (0.006)		
Investment c2 in 10000s * Main Selling Period		0.013 (0.008)	
Investment c3 in 10000s * Main Selling Period			0.004 (0.004)
Investment c1 in 10000s Sqr	−0.0005*** (0.0002)		
Investment c1 in 10000s * Main Selling Period	0.008 (0.008)		
Investment c2 in 10000s Sqr		−0.001 (0.0004)	
Investment c3 in 10000s Sqr			−0.0001* (0.0001)
Observations	128	128	128
R^2	0.905	0.875	0.915
Adjusted R^2	0.899	0.867	0.910
Note:			*p<0.1; **p<0.05; ***p<0.01

Before summarising the elasticity results, a brief discussion of the methodology used to compute the long-term elasticities is presented.

Since a log-level function form is used, there is no direct way of computing the long-term elasticities; the long-term elasticity was computed by simulating a 10% increase in the communication spend. The rise in communication spend was simulated for a specific day, and the increase in sales was recorded for the next ten weeks. This procedure was carried out for all possible days and the impact for the next ten weeks was averaged. This impact was accumulated, and the elasticity was calculated on the accumulated impact of 10 weeks.

Table 10: Own Advertising Elasticity Summary

	OLS		IV	
Fragrance	Short Term Elasticity	Long Term Elasticity	Short Term Elasticity	Long Term Elasticity
c1 Si	0.0040	0.04	0.0182	0.16
c2 Black Opium	0.0021	0.02	0.0210	0.2
c3 La Vie Est Belle	0.0042	No Effect	0.0096	No Effect

In general IV estimates are much higher compared to OLS estimates. This result can be due to the endogeneity problem in communication expenditure. According to the OLS estimates c3 is relatively the most responsive in short-term. However, in the long term, c1's communication is much more responsive. c3's lag variable was not statistically significant thus it does not have a long-term impact.

The following table shows the diagnostic test results for IV models. The results are satisfactory for c1 and c2. However, these results suggest that OLS is consistent for c3's regression model. This observation is also supported by a smaller difference in the two estimates compared to the estimates of the other two fragrances.

Table 11: IV Regression Model's Diagnostics (P-Value) for Own Communication Impact

Fragrance	Weak Instrument Test*	Wu-Hausman Test†	Sargan Test‡
c1 Si	0.0001076	0.0242206	0.5043228
c2 Black Opium	0.0078324	0.0005936	0.4364356
c3 La Vie Est Belle	0.0003423	0.3247865	0.5735497
Null Hypothesis * Instruments not Relevant; † OLS is consistent; ‡ Instruments are valid;			

Coming over to the IV estimates for advertising elasticity, c2 is relatively the most elastic in both short as well as in the long-term. c3 still doesn't appear to have a long-term impact. For full regression results please refer to Appendix A Table 24: IV (Own Communication Impact).

2.2.2 Cross Communication Impact

2.2.2.1 Investment Models

The condensed regression output below shows the cross-communication impact of the three focal brands (for more information, please refer to Appendix A Table 25: OLS (Cross Communication Impact)). It is surprising to note that most of the significant cross-impact is positive. For instance, the table below suggests that a $100000 communication investment by c3 will not only increase c3's Sales by 7%, but it will also increase c1's Sales by 6%. This result can be explained by the use of "bundling" by the "focal" brands. It was indeed the case in 2015 that the fragrances by the focal brand were offered as a bundled purchase (Mortimer 2015).

Table 12: OLS (Cross Communication Impact) Condensed

	Dependent variable:		
	L c1 Sales Quanitity	L c2 Sales Quanitity	L c3 Sales Quanitity
	(1)	(2)	(3)
Investment c1 in 10000s	0.008^{***}	-0.0002	0.005^{**}
	(0.003)	(0.004)	(0.003)
Investment c2 in 10000s	0.002	0.013^{***}	-0.004^{*}
	(0.003)	(0.003)	(0.002)
Investment c3 in 10000s	0.006^{***}	0.007^{***}	0.007^{***}
	(0.001)	(0.002)	(0.001)
Observations	128	128	128
R^2	0.910	0.882	0.914
Adjusted R^2	0.905	0.875	0.909
Note:			*p<0.1; **p<0.05; ***p<0.01

Moving on to the advertising elasticities, the table below shows the elasticity matrix for both short and long-term. Since c3's lag variable was not significant, there is no long-term impact. It is interesting to see that the coss advertising elasticities are close to the own advertising elasticities. This result is a stronger suggestion of the bundling phenomenon at play.

Table 13: Cross Advertising Elasticity Matrix Summary

	Short Term			Long Term		
	c1	c2	c3	c1	c2	c3
c1	0.0063	No Effect	0.0035	0.127	No Effect	No Effect
c2	No Effect	0.007	-0.0020	No Effect	0.116	No Effect
c3	0.0051	0.006	0.0058	0.126	0.115	No Effect

IV regression models were also computed, but as shown below in the table, models for c1 and c3 failed to reject the consistency of OLS at 5% significance level. Further, most of the investment impacts were not identified while using IV which can be caused due to a high correlation between the instruments. This is the reason why IV models for this section were excluded from this report.

Table 14: IV Regression Model's Diagnostics (P-Value) for Cross Communication Impact

Fragrance	Weak Test 1*	Weak Test 2*	Weak Test 3*	Wu-Hausman Test†	Sargan Test‡
c1 Si	0.0002411	0.0031059	0.0004013	0.0806251	0.2730748
c2 Black Opium	0.0004062	0.0000466	0.0002676	0.0340469	0.9053423
c3 La Vie Est Belle	0.0006752	0.0324786	0.0013351	0.6004920	0.6230714

Null Hypothesis * Instruments not Relevant; † OLS is consistent; ‡ Instruments are valid;

2.2.2.2 Adstock Models

Adstock for all the three fragrances was calculated. As shown below the optimised alpha for each of the fragrances was quite similar to each other.

Table 15: Adstock Alpha Values

Fragrance	Optimised.Alpha
c1 Si	0.63
c2 Black Opium	0.73
c3 La Vie Est Belle	0.64

Further, the condensed regression output shows similar results obtained using investment models(for more information, please refer to Appendix A Table 26: OLS (Cross Communication Impact) using Adstock Models). The bundling effect is also consistent here since the cross-adstock impact is positive.

Table 16: OLS (Cross Communication Impact) using Adstock Models (Condensed)

	Dependent variable:		
	L c1 Sales Quanitity	L c2 Sales Quanitity	L c3 Sales Quanitity
	(1)	(2)	(3)
Adstock c1 in 10000s	0.008^{***}	-0.003	0.003^{**}
	(0.002)	(0.003)	(0.002)
Adstock c2 in 10000s	0.004^{***}	0.013^{***}	-0.002
	(0.002)	(0.003)	(0.001)
Adstock c3 in 10000s	0.003^{***}	0.004^{***}	0.006^{***}
	(0.001)	(0.001)	(0.001)
Observations	128	128	128
R^2	0.917	0.881	0.922
Adjusted R^2	0.912	0.874	0.918
Note:			$^{*}p<0.1$; $^{**}p<0.05$; $^{***}p<0.01$

IV regression models were also computed using adstock, but they faced similar issues discussed in the previous section.

2.3 Competitive Effects

A metric similar to market share was calculated to assess the competitive effects. The difference is that the size of the market here was the total sales of the three focal brands. This change was made as data on aggregate market value was not able for all the periods.

Further to this, the table below shows the stationarity test p-values for the time series of the relative size of the focal brands. We can see that the time series is stationary and thus we can use its lag variable in our models.

Table 17: Stationarity Test Results (P-Value) for Relative Size of the Focal Brands

Fragrance	ADF*	PP†	KPSS‡	Conclusion
c1 Si	0.3632736	0.0117584	0.0100000	Stationary
c2 Black Opium	0.5990441	0.1688582	0.0951285	Stationary
c3 La Vie Est Belle	0.1751376	0.0100000	0.0100000	Stationary
Null Hypothesis * Unit Root; † Unit Root; ‡ Stationary;				

Using the relative market share of the three focal brands as our dependent variable we get a regression output as expected. Cross investment variables have non-positive coefficients. This result suggests that these three focal brands are indeed competing with each other even when the bundling mechanism is in effect. An interesting observation from the condensed regression output below the fact that price variables of c1 and c2 have non-positive coefficients whereas c3's coefficient is positive.

Table 18: OLS (Competitive Effects) Condensed

	Dependent variable:		
	c1 Market Share	c2 Market Share	c3 Market Share
	(1)	(2)	(3)
Investment c1 in 10000s	0.001^{***}	-0.001^{***}	-0.0001
	(0.0002)	(0.0002)	(0.0003)
Investment c2 in 10000s	-0.0003	0.002^{***}	-0.002^{***}
	(0.0003)	(0.0002)	(0.0003)
Investment c3 in 10000s	-0.0004^{***}	-0.001^{***}	0.001^{***}
	(0.0001)	(0.0001)	(0.0001)
Price c1	-0.002^{**}		
	(0.001)		
Price c2		-0.001	
		(0.001)	
L Price c3			0.002^{*}
			(0.001)
Observations	128	128	128
R^2	0.789	0.868	0.817
Adjusted R^2	0.780	0.862	0.810
Note:			$^{*}p<0.1$; $^{**}p<0.05$; $^{***}p<0.01$

Further, the IV diagnostics below show that OLS is consistent and thus IV models were omitted.

Table 19: IV Regression Model's Diagnostics (P-Value) for Competitive Effects

Fragrance	Weak Test 1*	Weak Test 2*	Weak Test 3*	Wu-Hausman Test†	Sargan Test‡
c1 Si	0	0	0	0.1297798	0.9113493
c2 Black Opium	0	0	0	0.0160310	0.8017954
c3 La Vie Est Belle	0	0	0	0.8703594	0.7287805
Null Hypothesis * Instruments not Relevant; † OLS is consistent; ‡ Instruments are valid;					

2.4 Advice on Budget Allocation and Optimisation for the Rest of the Year 2017

This section is divided into two subsections: Pricing and Communication Strategy.

2.4.1 Pricing Strategy

c1 Si

As indicated by the Clout and Vulnerability Map in section 2.1.2, c1 Si has a relatively stronger position in the market. Therefore c1 can be a price setter in the fragrance market in Italy. Further, c1's price elasticity of -7.66 according to OLS estimates suggests that its customers are price elastic, and a small decrease in price can help c1 increase its revenue by a lot (for more information, please refer to Table 13: Cross Advertising Elasticity Matrix Summary). Further c1's price elasticity is unchanged in peak periods, and this should be considered into account while formulating a pricing strategy. Having said that c1 could decrease the price in main selling periods to achieve the maximum increase in its revenue. In the rest of 2017, c1 can drop its price in December to take advantage of the surge in demand.

c2 Black Opium

Gaining insight from the Clout and Vulnerability Map, c2 should watch out for the price of c1 Si since it has a large and a significant impact on the sales quantity for c2's fragrance. For every 1% decrease in c1 Si's price c2 loses out on 2.34% of its sales. Since c2's own price elasticity is highly elastic (-4.82), c2 should also decrease its price in the main selling periods (for more information, please refer to Table 13: Cross Advertising Elasticity Matrix Summary). Similar to c1, c2 should introduce a price drop in December to take advantage of the surge in demand.

c3 La Vie Est Belle

The Clout and Vulnerability Map suggests that c3 caters to a different customer base and thus it can also act as a price setter in the market. Further, it is interesting to note that c3's price elasticity is inelastic (-0.44) suggesting that c3's customer in Italy might be less responsive to a price change. The inelastic price elasticity can be due to c3's brand value or the taste and preferences of the Italian customers. This observation is further supported by the fact that price variable of c3 has a positive coefficient in the competitive OLS models (for more information, please refer to Table 18: OLS (Competitive Effects) Condensed). The inelastic nature of c3's price can help increase c3's revenue by increasing its price. It is interesting to note that c3's price elasticity turns highly elastic in peak periods (-3.89) (Table 7: Own Price Elasticity Summary). Thus, c3 should increase its price in normal periods and decrease it in peak periods to attain higher revenue.

2.4.2 Communication Strategy

c1 Si

Interestingly, the responsiveness of customers towards c1's Communication is the same in both peak and normal periods. This suggests that c1 should advertise heavily in peak periods. Having said that c1's communication spend has a diminishing return property. Therefore, c1 shouldn't spend more than 520,000 on communication (Obtained by using first differentiation, for more information, please refer to Table 9: OLS (Own Communication Impact) Condensed).

c1's alpha value or the memory effect is also sizeable (0.63) suggesting that c1 can stop spending on communication towards the end of December. This strategy is justified because the memory effect will tail off rather than cutting off sharply. Although the bundling mechanism helps increase c1's sales when c3 increases its communication spend, It is quintessential to note that it has a negative impact on the relative market share for c1. This negative impact suggests that although c3's communication spend increase c1 Si's sales, it has a cannibalising impact on c1 Si's relative market share.

c2 Black Opium

Similar to c1, c2 also doesn't have a different impact of communication in peak periods. Therefore, c2 should try to maximise its return from communication expenditure by clustering its expenditure near the peak sales period. Unlike c1, c2 doesn't have a significant diminishing return property. However, c2 should be cautious in spending a lot.

Coming over to the memory effect, c2 has the highest alpha (0.73). Therefore, it can stop advertising even before c1 as c2's memory effect would take longer to tail off. The higher alpha can help c2 to save cost as c2 doesn't have to advertise as frequently as the other focal brands to maintain a specific adstock level. c2 also experience the same cannibalising impact and therefore should watch out for investment done by its focal competitors.

c3 La Vie Est Belle

c3's communication follows a similar pattern as described above. Its communication response doesn't change in the peak periods. Therefore, most of its investment should be clustered near main selling periods. Like c1, it also experiences the diminishing return property. However, the diminishing point (1,300,000) is much higher compared to c1's diminishing point (520,000).

c3's alpha is 0.64. Thus it should also stop investing heavily before the peak season is over. Further, c3 should watch out for c2's investment as c2 has a cannibalising impact on its sales (for more information, please refer to Table 18: OLS (Competitive Effects) Condensed).

3 Conclusion

This study finds that the price in the fragrance market in Italy is elastic with c3 being the exception in normal periods. Furthermore, customers become more responsive to prices in peak periods. This insight can be exploited by the fragrance brands to optimise their timing of price reductions.

There are diminishing returns for the communication expenditure incurred by a majority of the focal brands. Further, fragrance brands need to tackle bundling options carefully as there can still be competitive effects in the market.

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Appendix A

Table 20: OLS (Own Price Elasticity)

	Dependent variable:		
	L c1 Sales Quanitity	L c2 Sales Quanitity	L c3 Sales Quanitity
	(1)	(2)	(3)
Week Number	-0.002^{**}	0.002^{***}	0.0003
	(0.001)	(0.001)	(0.001)
Main Selling Period	0.974	-9.582	16.512^{**}
	(4.660)	(10.082)	(7.891)
L Price c1	-1.681^{***}		
	(0.560)		
Investment c1 in 10000s	0.013^{***}		
	(0.002)		
L Price c2		-3.966^{***}	
		(0.557)	
Investment c2 in 10000s		0.016^{***}	
		(0.003)	
L Price c3			-1.535^{**}
			(0.654)
Investment c3 in 10000s			0.008^{***}
			(0.001)
Google Trend - Profumo	0.021^{***}	0.014^{***}	0.026^{***}
	(0.002)	(0.003)	(0.002)
L Lag c1 Sales Quantity	0.091		
	(0.071)		
L Price c1 * Main Selling Period	-0.165		
	(1.116)		
L Lag c2 Sales Quantity		0.378^{***}	
		(0.098)	
L c2 c1 * Main Selling Period		2.322	
		(2.404)	
L Lag c3 Sales Quantity			0.029
			(0.072)
L Price c3 * Main Selling Period			-3.937^{**}
			(1.912)
Constant	13.413^{***}	20.745^{***}	13.548^{***}
	(2.321)	(2.646)	(2.766)
Observations	128	128	128
R^2	0.901	0.875	0.916
Adjusted R^2	0.895	0.868	0.912
Note:			$^{*}p<0.1$; $^{**}p<0.05$; $^{***}p<0.01$ L stands for Log

Table 21: IV (Own Price Elasticity)

	Dependent variable:		
	L c1 Sales Quanitity	L c2 Sales Quanitity	L c3 Sales Quanitity
	(1)	(2)	(3)
Week Number	−0.001	0.002***	0.00002
	(0.001)	(0.001)	(0.001)
L Price c1	−1.743***		
	(0.667)		
L Price c2		−4.043***	
		(0.743)	
L Price c3			−1.048
			(0.756)
Main Selling Period	0.892	−8.620	16.279**
	(5.025)	(13.015)	(6.624)
Investment c1 in 10000s	0.024***		
	(0.006)		
Investment c2 in 10000s		0.033***	
		(0.011)	
Investment c3 in 10000s			0.012***
			(0.004)
Google Trend - Profumo	0.016***	0.007	0.023***
	(0.004)	(0.006)	(0.004)
L Lag c1 Sales Quantity	0.118*		
	(0.061)		
L Price c1 * Main Selling Period	−0.171		
	(1.205)		
L Lag c2 Sales Quantity		0.390***	
		(0.086)	
L Price c2 * Main Selling Period		2.083	
		(3.109)	
L Lag c3 Sales Quantity			0.064
			(0.067)
L Price c3 * Main Selling Period			−3.887**
			(1.604)
Constant	13.545***	21.102***	11.307***
	(2.741)	(3.329)	(3.199)
Observations	128	128	128
R^2	0.870	0.821	0.906
Adjusted R^2	0.862	0.810	0.901
Note:			*p<0.1; **p<0.05; ***p<0.01 L stands for Log

Table 22: OLS (Cross Price Elasticity)

	Dependent variable:		
	c1 Sales Quanitity	c2 Sales Quanitity	L c3 Sales Quanitity
	(1)	(2)	(3)
Main Selling Period	−99,505.390	614.272	
	(89,668.870)	(485.099)	
L Price c1	−14,493.310***		
	(2,111.606)		
L Price c2	2,771.485	−7,102.778***	
	(2,023.717)	(1,513.589)	
Price c1			0.015*
			(0.009)
Price c3			−0.057***
			(0.012)
Google Trend - Profumo	206.463***	169.240***	0.034***
	(24.560)	(15.440)	(0.002)
Lag c1 Sales Quantity	−0.128		
	(0.102)		
L Price c1 * Main Selling Period	−13,671.810*		
	(7,186.366)		
L Price c2 * Main Selling Period	37,503.140		
	(24,298.740)		
Constant	45,154.330***	26,643.090***	9.884***
	(7,080.924)	(6,450.232)	(0.479)
Observations	128	129	129
R^2	0.890	0.870	0.862
Adjusted R^2	0.883	0.867	0.858
Note:			*p<0.1; **p<0.05; ***p<0.01 L stands for Log

Table 23: OLS (Own Communication Impact)

	Dependent variable:		
	L c1 Sales Quanitity	L c2 Sales Quanitity	L c3 Sales Quanitity
	(1)	(2)	(3)
Investment c2 in 10000s		0.029**	
		(0.012)	
Investment c3 in 10000s			0.013***
			(0.004)
Google Trend - Profumo	0.020***	0.013***	0.025***
	(0.002)	(0.003)	(0.002)
Investment c1 in 10000s	0.026***		
	(0.006)		
L Lag c2 Sales Quantity		0.413***	
		(0.086)	
Investment c2 in 10000s * Main Selling Period		0.013	
		(0.008)	
L Lag c3 Sales Quantity			0.034
			(0.069)
Investment c3 in 10000s * Main Selling Period			0.004
			(0.004)
Main Selling Period	0.124	0.057	0.122
	(0.202)	(0.166)	(0.126)
Investment c1 in 10000s Sqr	−0.0005***		
	(0.0002)		
L Price c1	−2.773***		
	(0.283)		
L Lag c1 Sales Quantity	0.129**		
	(0.057)		
Investment c1 in 10000s * Main Selling Period	0.008		
	(0.008)		
Investment c2 in 10000s Sqr		−0.001	
		(0.0004)	
L Price c2		−2.837***	
		(0.440)	
Investment c3 in 10000s Sqr			−0.0001*
			(0.0001)
L Price c3			−1.558***
			(0.315)
Constant	17.582***	15.875***	13.621***
	(1.388)	(2.164)	(1.548)
Observations	128	128	128
R^2	0.905	0.875	0.915
Adjusted R^2	0.899	0.867	0.910
Note:			*p<0.1; **p<0.05; ***p<0.01 L stands for Log

Table 24: IV (Own Communication Impact)

	Dependent variable:		
	L c1 Sales Quanitity	L c2 Sales Quanitity	L c3 Sales Quanitity
	(1)	(2)	(3)
Investment c2 in 10000s		0.041***	
		(0.013)	
L Price c2		−2.373***	
		(0.736)	
Investment c3 in 10000s			0.012***
			(0.004)
L Price c3			−1.394***
			(0.385)
Google Trend - Profumo	0.015***	0.007	0.024***
	(0.004)	(0.007)	(0.004)
Investment c1 in 10000s	0.025***		
	(0.006)		
Main Selling Period	0.156		0.178**
	(0.126)		(0.075)
L Price c1	−2.643***		
	(0.354)		
L Lag c1 Sales Quantity	0.136**		
	(0.061)		
L Lag c2 Sales Quantity		0.416***	
		(0.094)	
L Lag c3 Sales Quantity			0.042
			(0.075)
Constant	17.107***	13.998***	12.909***
	(1.694)	(3.346)	(1.843)
Observations	128	128	128
R^2	0.864	0.742	0.903
Adjusted R^2	0.859	0.733	0.899
Note:			*p<0.1; **p<0.05; ***p<0.01 L stands for Log

Table 25: OLS (Cross Communication Impact)

	Dependent variable:		
	L c1 Sales Quanitity	L c2 Sales Quanitity	L c3 Sales Quanitity
	(1)	(2)	(3)
Main Selling Period	0.254**	0.140	0.174**
	(0.104)	(0.139)	(0.082)
L Price c1	−2.754***		
	(0.331)		
L Price c2		−2.606***	
		(0.385)	
L Price c3			−1.644***
			(0.321)
Google Trend - Profumo	0.017***	0.014***	0.027***
	(0.002)	(0.003)	(0.002)
Investment c1 in 10000s	0.008***	−0.0002	0.005**
	(0.003)	(0.004)	(0.003)
Investment c2 in 10000s	0.002	0.013***	−0.004*
	(0.003)	(0.003)	(0.002)
Investment c3 in 10000s	0.006***	0.007***	0.007***
	(0.001)	(0.002)	(0.001)
L Lag c1 Sales Quantity	0.135*		
	(0.071)		
L Lag c2 Sales Quantity		0.387***	
		(0.089)	
L Lag c3 Sales Quantity			0.001
			(0.073)
Constant	17.529***	15.041***	14.211***
	(1.707)	(1.926)	(1.567)
Observations	128	128	128
R^2	0.910	0.882	0.914
Adjusted R^2	0.905	0.875	0.909
Note:			*p<0.1; **p<0.05; ***p<0.01
			L stands for Log

Table 26: OLS (Cross Communication Impact) using Adstock Models

	Dependent variable:		
	L c1 Sales Quanitity	L c2 Sales Quanitity	L c3 Sales Quanitity
	(1)	(2)	(3)
Main Selling Period	0.286***	0.136	0.212***
	(0.077)	(0.112)	(0.063)
L Price c1	−3.534***		
	(0.362)		
L Price c2		−3.704***	
		(0.490)	
L Price c3			−1.791***
			(0.319)
Google Trend - Profumo	0.017***	0.018***	0.025***
	(0.002)	(0.003)	(0.002)
Adstock c1 in 10000s	0.008***	−0.003	0.003**
	(0.002)	(0.003)	(0.002)
Adstock c2 in 10000s	0.004***	0.013***	−0.002
	(0.002)	(0.003)	(0.001)
Adstock c3 in 10000s	0.003***	0.004***	0.006***
	(0.001)	(0.001)	(0.001)
L Lag c1 Sales Quantity	−0.165*		
	(0.095)		
L Lag c2 Sales Quantity		0.088	
		(0.132)	
L Lag c3 Sales Quantity			−0.170**
			(0.080)
Constant	22.984***	21.638***	16.219***
	(2.043)	(2.697)	(1.529)
Observations	128	128	128
R^2	0.917	0.881	0.922
Adjusted R^2	0.912	0.874	0.918
Note:			*p<0.1; **p<0.05; ***p<0.01 L stands for Log

Table 27: OLS (Competitive Effects)

	Dependent variable:		
	c1 Market Share	c2 Market Share	c3 Market Share
	(1)	(2)	(3)
Investment c1 in 10000s	0.001***	−0.001***	−0.0001
	(0.0002)	(0.0002)	(0.0003)
Investment c2 in 10000s	−0.0003	0.002***	−0.002***
	(0.0003)	(0.0002)	(0.0003)
Investment c3 in 10000s	−0.0004***	−0.001***	0.001***
	(0.0001)	(0.0001)	(0.0001)
Price c1	−0.002**		
	(0.001)		
Lag Market Share c1	0.750***		
	(0.060)		
Price c2		−0.001	
		(0.001)	
Lag Market Share c2		0.863***	
		(0.034)	
Price c3			0.002*
			(0.001)
Lag Market Share c3			0.789***
			(0.041)
Constant	0.183***	0.110*	−0.008
	(0.059)	(0.058)	(0.062)
Observations	128	128	128
R^2	0.789	0.868	0.817
Adjusted R^2	0.780	0.862	0.810
Note:			*p<0.1; **p<0.05; ***p<0.01

Appendix - B

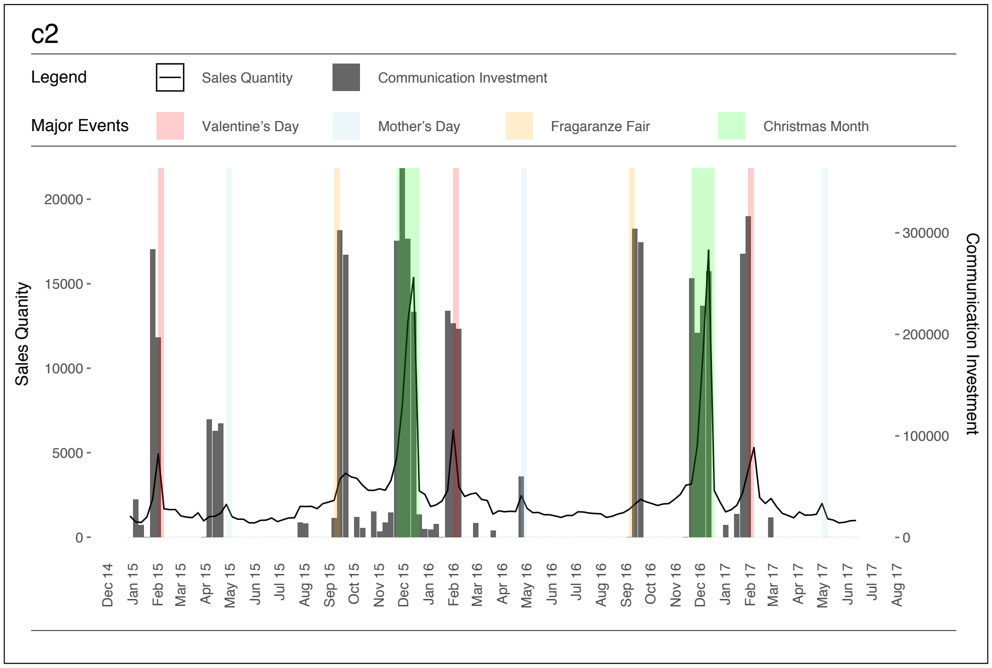

Figure 4: c2 Black Opium Sales Quanity and Communication Investment along with Major Perfume Selling Periods in Italy

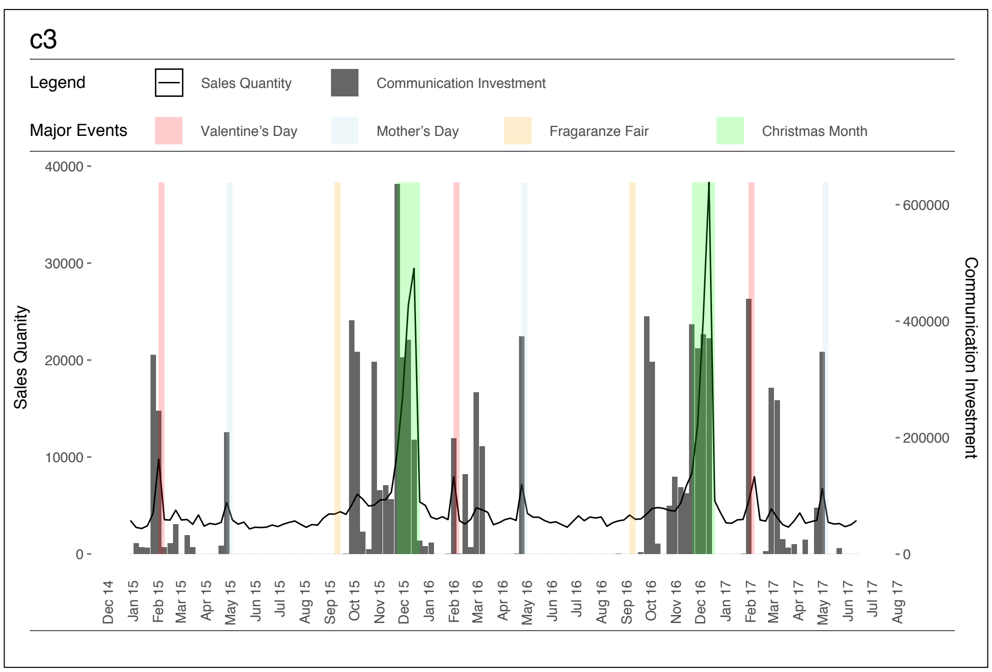

Figure 5: c3 La Vie Est Belle Sales Quanity and Communication Investment along with Major Perfume Selling Periods in Italy